The Springer Series on Demographic Methods and Population Analysis 37

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A Practitioner's Guide to State and Local Population Projections

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Foreword

A large part of our daily lives is governed by numbers. How many hours of sleep did I get last night? How many unread messages are queued up in my inbox? How many "friends" do I have on Facebook? What's the upcoming Powerball payoff? How's my cholesterol count doing? Can I recall my daughter's phone number, my granddaughter's birthday? Numbers such as these encompass portions of our personal and shared social reality. They roll around in our head, and they are part of what determine our mood, our behavior, well-being, worries, and activity constraints.

Population projections also present us with numbers. But these are numbers of a very different nature. Rather than simply *reflecting* a social reality (and associated beliefs and behaviors), they serve to *create* a reality based on anticipation—a reality unwitnessed, unobserved, and largely unknown. Yet, on the basis of such numbers, schools are built (or closed), roads are widened, airport terminals expanded, municipal services extended, and marketing strategies altered. So this book is about the second kind of number, the sort leading to anticipatory behaviors and, occasionally, preemptive actions. It is the applied demographer's difficult role to creatively deploy the data, tools, and perspectives of the population sciences to carry out these tasks not only ethically and transparently but with an experienced and disciplined hand. This book provides a marvelously clear, well-organized, and comprehensive blueprint for understanding and competently performing this role.

The authors are seasoned applied demographic practitioners. They have individually and collaboratively contributed mightily to the demographic literature. The book is intellectually solid, methodologically encompassing, and—while retaining the historically interesting material—firmly contemporary and up to date.

Early in my own career, one of my mentors rhetorically asked, "Why do we make population projections? They always turn out to be wrong, so why do we persist?" After a brief excursion through the standard reasons for why projections are useful, he added, "Probably the most important reason for engaging in this enterprise is so that we later know what to be surprised about." Wonderfully said! The point is that we live in a world of frenetic change. We are so habituated to mindlessly accommodating to this change that we rarely pause long enough to say "Wow!" and to reflect on what we thought, just a few years back, our present reality might look like. Projections and forecasts prepared yesterday permit us to do that today. Today's projections will serve that potentially chastening purpose tomorrow.

The overall narrative and thoroughly developed methodologies in *A Practitioner's Guide to State and Local Population Projections* will, of course, not eliminate all of tomorrow's surprises. One can indeed hope, however, that practitioners who wisely select to use this book to guide their own demographic pursuits will benefit from the authors' skillful verve, their richly detailed methodological coverage, and the numerous concrete examples presented throughout the material to minimize the number and magnitude of future surprises.

This valuable compendium presents methods that are tried and tested alongside those that are recent and innovative. The book revisits and updates most of the topics treated in the authors' earlier book, *State and Local Population Projections: Methodology and Analysis*. However, the current book should not be understood as a revised edition. Fresh attention is given to emerging methodological approaches in small-area population forecasting (projecting) and, in particular, to new data resources that have fundamentally altered the information content of forecasting models. The material is treated with originality and conviction and benefits immensely from real-life illustrations drawn from the authors' own work. With *A Practitioner's Guide to State and Local Population Projections*, Smith, Tayman, and Swanson have again secured their leading place as careful, practical, and solidly competent applied demographic scholars.

University of North Carolina at Chapel Hill Paul R. Voss
June 2013

Preface

A lot has happened since we published *State and Local Population Projections: Methodology and Analysis* in 2001. Smart phones, electronic tablets, and the Cloud have given us access to virtually endless sources of information, no matter where we are. Improvements in technology, software, and computing hardware have expanded the way we access, store, and analyze information. Facebook, Twitter, and other social media sites have changed the way we communicate. Globalization has altered the world's economic system and 9/11 changed almost everything, from international relations to the way we board airplanes.

A lot has happened in the field of applied demography as well. Data sources have proliferated, methods have advanced, computing capabilities have mushroomed, and new research has been published. One major change is that the decennial census no longer includes a long form collecting detailed socioeconomic, demographic, and housing information from a sample of census respondents. This information is now collected in the American Community Survey (ACS), which differs in several ways from the census long form. Particularly important for the production of population projections is that the ACS collects data continuously rather than once per decade, is based on a smaller sample size, uses different residence rules, and measures migration over a 1-year rather than a 5-year period.

These and other changes have convinced us that a new book on state and local population projections is needed. This new book retains and updates much of the material included in our previous book, but covers a number of new topics as well. We present a detailed discussion of the differences between ACS migration data and the migration data collected in the decennial census, paying particular attention to how these differences affect the construction of cohort-component projections. We provide an illustration of how to use ACS migration data to project a county population. We add a new chapter on projections of population-related variables such as households, school enrollment, labor force participation, and persons with disabilities. We expand our discussion of microsimulation models, scenario analysis, special populations, international migration, and the benefits of combining projections from several different models. Throughout the book, we incorporate research findings that have appeared in the literature since the publication of our previous book.

As before, we pay particular attention to problems encountered when making projections for small areas (e.g., counties and subcounty areas). We describe a number of data sources and projection methods, focusing on those that are most accessible and can be used in a variety of circumstances. We discuss the strengths and weaknesses of each and provide our thoughts on which are most useful for particular purposes. We include many examples and illustrations, as well as equations and verbal descriptions, in an attempt to present the material as clearly as possible.

A number of methods, data sources, and application techniques can be used for constructing state and local population projections. Deciding which ones to include—and how to present them—was not an easy task. We wanted the book to be comprehensive but not long-winded, technically precise but not overly mathematical, clearly written but not simplistic. We wanted it to be useful to analysts with a strong background in demography yet accessible to those with little or no demographic training. Most important, we wanted it to provide practical guidance to demographers, planners, market analysts, and others called upon to construct or evaluate state and local population projections in real-world settings. The reader will have to decide whether we have succeeded in accomplishing these often-conflicting goals.

We thank Paul Voss for writing the foreword to this book. It would be impossible to find a person more qualified than Paul, given his numerous and important contributions to the field of applied demography. We also thank Evelien Bakker and Bernadette Deelen-Mans for shepherding the book through Springer's production process; their assistance was invaluable.

Above all, we express our gratitude to our wives—Rita, Melinda, and Rita—for their love, encouragement, and patience as we worked on this book.

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Chapter 1
Rationale, Terminology, Scope

People are fascinated by the future. Palm readers, astrologers, and crystal-ball-gazers down through the ages have found eager customers for their predictions and views of the future. Modern-day analysts and forecasters—using computers and mathematical models instead of tea leaves and chicken entrails—continue to find willing audiences. The desire to see into the future is seemingly insatiable and apparently has not been diminished by the relatively low success rates achieved by visionaries and forecasters in the past (see Box 1.1).

The desire to foresee future population trends reflects much more than idle curiosity. At the global level, many are concerned about the earth's ability to feed, clothe, and house the several billion people expected to be added to the world's population over the next 100 years. Nations and states are concerned about the economic, social, political, and environmental consequences of population growth and demographic change. At the local level, planning for schools, hospitals, shopping centers, housing developments, roads, and countless other projects is strongly affected by expected population growth. Indeed, the success or failure of such plans often depends on the extent to which projected growth is realized over time. It is no wonder that population projections are of so much interest to so many people.

Despite this high level of interest, the future is unknown and—in most respects—unknowable. Many factors influence population growth and demographic change, often in unpredictable ways. No matter how accurate our data and sophisticated our methodology, we still cannot "see" into the future. One hundred years ago, who could have predicted the baby boom and bust, the tremendous increase in life expectancy, or the dramatic shifts in foreign immigration that occurred in the United States during the twentieth century? Who could have predicted microwave ovens, interstate highways, space exploration, smart phones, or the Internet? For that matter, who could have predicted the appearance of hula hoops, pet rocks, Facebook, or Lady Gaga? As Winston Churchill noted, "the future is just one damn thing after another."

We are not completely lost, however. Although individual events may be unpredictable, patterns often emerge when the effects of individual events are

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Box 1.1 Blasts from the Past: Some Predictions that Missed the Boat

"I see no good reasons why the views given in this volume should shock the religious sensibilities of anyone."—Charles Darwin, *The Origin of Species*, 1869.

"This "telephone" has too many shortcomings to be seriously considered as a means of communication. The device is inherently of no value to us."—Western Union internal memo, 1876.

"Heavier-than-air flying machines are impossible."—Lord Kelvin, British scientist, 1899.

"Who the hell wants to hear actors talk?"—H.M. Warner, Warner Brothers, 1927.

"Stocks have reached what looks like a permanently high plateau."—Irving Fisher, Professor of Economics, Yale University, 1929.

"I think there is a world market for maybe five computers."—Thomas Watson, Chairman of IBM, 1943.

"We don't like their sound, and guitar music is on the way out."—Decca Recording Company, rejecting the Beatles, 1962.

"With over 50 foreign cars already on sale here, the Japanese auto industry isn't likely to carve out a big slice of the U.S. market."—*Business Week*, August 2, 1968.

"640 K ought to be enough for anybody."—Attributed to Bill Gates, founder of Microsoft, 1981, but perhaps urban legend.

combined. This is especially true in demography, where the momentum of demographic processes links the future with the past in clear and measurable ways. We can study demographic trends, collect historical data, and build projection models based on our knowledge of the past and our expectations for the future. Since the future has roots in the past, these projections will often provide reasonably accurate predictions of future population change. If constructed and interpreted properly, population projections can be very useful tools for planning and analysis.

1.1 What Is a Population Projection?

1.1.1 Projections, Forecasts, Estimates

A variety of terms can be used to describe calculations of past and future populations. Following demographic convention, we define a *population projection* as the numerical outcome of a particular set of assumptions regarding future population trends (Isserman and Fisher 1984; Keyfitz 1972; Pittenger 1976; Siegel 2002, p. 450; Weeks 2012, p. 344). Some projections refer to total population while others provide breakdowns by age, sex, race, and other characteristics. Some focus solely on changes in total population while others distinguish among the individual components of growth—births, deaths, and migration.

Strictly speaking, population projections are conditional statements about the future. They show what the population would be *if* particular assumptions were to hold true. However, they make no predictions as to whether those assumptions actually *will* hold true. By definition, population projections are always "right," barring a mathematical error in their calculation. Since they make no predictions regarding the future, they can never be proven wrong by future events.

A *population forecast*, on the other hand, is the projection the analyst (i.e., the person or agency making the projection) believes is most likely to provide an accurate prediction of the future population. Whereas projections are non-judgmental, forecasts are explicitly judgmental. They are unconditional statements reflecting the analyst's views regarding the optimal combination of data sources, projection techniques, and methodological assumptions, leavened by personal judgment. Unlike projections, population forecasts *can* be proven right or wrong by future events (or—to be more realistic—they can be found to have relatively small or large errors).

Demographers have traditionally used the term *projection* to describe calculations of the future population. There are several reasons for choosing this terminology. First, *projection* is a more inclusive term than *forecast*. A forecast is a particular type of projection; namely, the projection the analyst believes is most likely to provide an accurate prediction of the future population. Given this distinction, all forecasts are projections but not all projections are forecasts. Second—as we discuss later in this chapter—projections can serve other purposes besides predicting the future population; we believe the term *projection* facilitates the discussion of these alternative roles. Finally, demographers have often intended their calculations of future population to be merely illustrative rather than predictive; *projection* fits more closely with this intention than *forecast*.

We use both terms in this book, but use *projection* as the general term describing calculations of future population. We use *forecast* and *forecasting* when the discussion focuses on predicting the most likely course of future population change. We believe the critical factor is not the term itself, but rather the purposes for which projections and forecasts are used (e.g., describing a hypothetical scenario or selecting the most likely outcome).

A distinction can also be made between *projections* and *estimates*. This distinction is based on both temporal and methodological considerations. The most fundamental difference is that projections refer to the future whereas estimates refer to the present or the past. In addition, estimates can often be based on data for corresponding points in time. For example, estimates for 2012 made in 2013 can be based on data series—such as births, deaths, building permits, school enrollments, tax records, and Medicare enrollees—reflecting population growth through 2012. Projections for 2020 made in 2013, however, cannot use such data series because those series do not yet exist.

The distinction between estimates and projections is not always clear-cut. Sometimes no data are available for constructing population estimates. In these circumstances, methods typically used for population projections are used for population estimates. For example, calculations of a city's age-sex composition in 2012 made in 2013 may have to be based on the extrapolation of 2000–2010 trends because data series reflecting post-2010 changes in age-sex composition may not be available. Should these calculations be called *estimates* or *projections*?

In this book we refer to calculations extending beyond the date of the last observed data point as *projections*; calculations for all prior dates are called *estimates*. For example, if we have data through July 1, 2012, calculations for dates on or before that day are called *population estimates* and calculations for dates after that day are called *population projections*.

1.1.2 Alternative Approaches

There are many approaches to making population projections. Some are subjective, others objective. Some are simple, others very complex. Causal models compete with non-causal models. Data requirements range from small to large. Levels of disaggregation vary from minimal to elaborate. There are also a variety of ways to classify projection methods. Figure 1.1 shows the classification scheme we follow in this book.

A fundamental distinction in the general forecasting literature is between subjective and objective methods (Armstrong 1985). Subjective methods are those lacking a clearly defined process for analyzing data and creating projections. Examples include projections based on general impressions, intuition, personal experience, or analogy; sometimes they are simply wild guesses. Even when subjective methods are based partly on objective data and formal analyses, the exact nature of the projection process is not clearly specified and cannot be replicated by other analysts.

Objective methods are those in which the projection process has been clearly specified. Data sources, assumptions, and mathematical relationships are defined in precise quantitative terms. Theoretically, the process can be specified so precisely that other analysts could replicate the method and obtain exactly the same results.

Although subjective methods are used frequently for some types of forecasting (e.g., technological change, geopolitical events), they are not commonly used for population projections. In this book, we focus primarily on objective methods. However, it is important to recognize that objective methods themselves contain many subjective elements. All projection methods require choices regarding data sources, time periods, functional forms, and so forth; that is, they all require the application of judgment. In general, the more complex the method, the greater the role of judgment in the projection process.

We describe four types of objective population projection methods: trend extrapolation, cohort-component, structural modeling, and microsimulation. *Trend extrapolation* methods are based on the continuation of readily observable historical trends. They can be simple (e.g., linear extrapolation) or complex (e.g., ARIMA time series models). They are often used for projections of total population, but can also be used for projections of a particular population subgroup (e.g., a racial or ethnic group) or a particular component of growth (e.g., births or deaths). Trend extrapolation methods are generally applied to a single data series (e.g., total

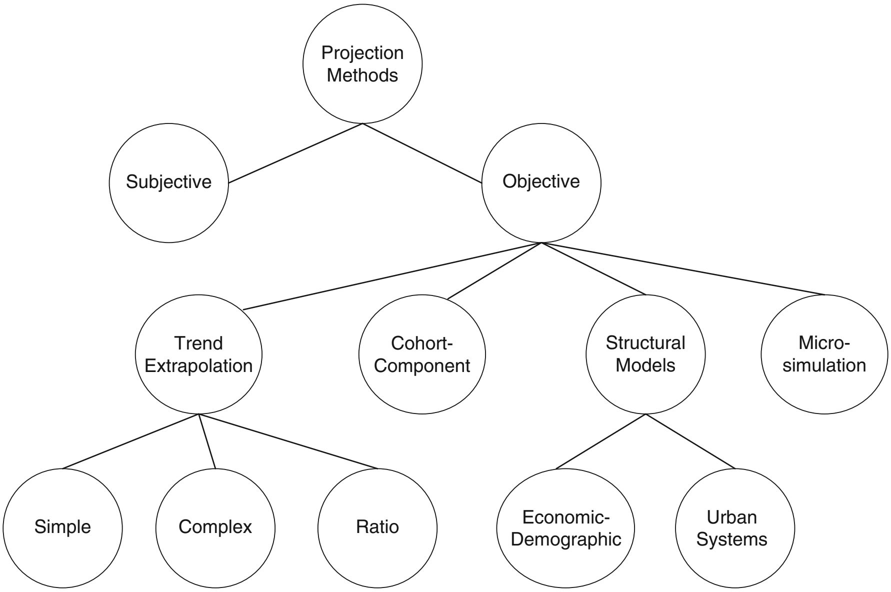

Fig. 1.1 A typology of population projection methods

population), but can also be applied to data expressed as ratios (e.g., a county's population as a share of the state's population). The defining characteristic of trend extrapolation methods is that projected values for a particular variable are based solely on historical values of that variable.

The *cohort-component* method accounts separately for births, deaths, and migration—the components of population growth. Most applications of this method divide the population into age-sex groups (i.e., cohorts) and project the components of growth separately for each cohort. The population can be further subdivided by race, ethnicity, and other demographic characteristics. There are a number of ways to construct cohort-component models and to project each component of growth. Since the cohort-component method is used more frequently than any other method of population projection, it is a major focus of this book.

Structural models focus on causal relationships between demographic and non-demographic variables. Their defining characteristic is that projected values for a demographic variable are based not only on its historical values, but on other variables as well. In many instances, the non-demographic variables are economic in nature. For example, we might develop a model in which job growth in one geographic area attracts migrants from another geographic area. This model might specify how many migrants arrive each year for each 1,000 new jobs created. Such a model has both economic and demographic components and translates projections of future job growth into projections of future migration. Whereas trend extrapolation models tell us nothing about the causes of population change, structural models provide explanations as well as projections of future change.

Many types of structural models can be developed, ranging from simple recursive models involving only a few variables and a single equation to huge systems of simultaneous equations involving many variables and parameters. In this book we discuss *economic-demographic* and *urban systems* models, the two types of structural models used most frequently for state and local population projections.

Microsimulation models focus on individual households and people rather than on demographic groups. Each individual is treated as an autonomous entity and interactions among individuals are accounted for using stochastic or deterministic parameters reflecting individual preferences, behaviors, and tendencies. The motivation behind these models is that aggregate behavior is composed of decisions made by many individuals and that these decisions provide a basis for projecting aggregate behavior. Microsimulation has a long history as a tool for policy analysis and is increasingly being used as a population projection method.

These four approaches—trend extrapolation, cohort-component, structural modeling, and microsimulation—are not mutually exclusive. Many projection models combine elements from several approaches. For example, some cohort-component models use structural models to project in- and out-migration while others simply extrapolate previous migration trends. Although trend extrapolation methods can be applied independently of the other two approaches, cohort-component and structural models are generally used in combination with another approach. Microsimulation models sometimes incorporate only demographic factors, but often incorporate non-demographic factors as well.

We discuss a wide variety of methods, models, and techniques in this book, including those most commonly used for state and local population projections. The ones we do not discuss either are not commonly used or are simply variants of other methods. We believe these methods, models, and techniques reflect the current "state of the art" and provide the reader with an ample set of tools for making state and local population projections.

1.2 Why Make Population Projections?

1.2.1 Roles of Projections

1.2.1.1 Predicting Future Population Change

Population projections can play a number of roles. The most fundamental is to predict future population change. Most data users (especially at the local level) use projections as a guide for decision making, viewing them as forecasts regardless of the intentions of the analyst(s) producing the projections. We give several examples of the use of projections for decision-making purposes in the next section. When projections are used in this manner, it is imperative to pay close attention to the plausibility of the underlying assumptions. If the assumptions are implausible, the projections will not provide credible forecasts.

1.2.1.2 Analyzing Determinants of Population Change

Projections are often used as a tool to analyze the determinants of population change. This is the "what if" role of projections. What effect would a 10% increase or decline in birth rates have on a state's population size and age composition? What would be the effect of the elimination of all cancer deaths? What effect would the opening of a new factory employing 2,000 people have on a county's migration patterns? What effect would future changes in demographic characteristics have on government programs and infrastructure needs? In this "simulation" role, projections are not meant to predict future population changes, but rather to illustrate the effects of specific changes in the model's underlying assumptions.

1.2.1.3 Presenting Alternative Scenarios

The third role of projections is closely related to the second. Projections can be used not only to analyze the determinants of population change, but also to give the data user an indication of potential future scenarios. Since we cannot be sure what the future will bring, it is helpful to consider projections based on various combinations of assumptions. Charting the implications of different combinations of assumptions gives the data user some idea of the potential variation in future population values. These alternative scenarios are often based on expert judgment regarding the appropriate combination of assumptions, but can also be based on formal techniques, giving the data user a probabilistic description of the uncertainty inherent in a particular projection (i.e., a *prediction interval*).

1.2.1.4 Promoting Agendas and Sounding Warnings

Projections can also be used to support a particular political or economic agenda or to sound a warning. Here the emphasis shifts from what *will* happen to what *could* or *should* happen. For example, suppose that a county's population has been projected to grow by 40% during the next 10 years. The county commission might use those projections of rapid growth as a marketing tool to attract new businesses to the area. Conversely, a citizen's group concerned about the environment might use those projections as a warning and a call for action to reduce the rate of growth. This role illustrates the political nature of population projections, a characteristic that may affect how projections are made and how they are used.

1.2.1.5 Providing a Base for Other Projections

Finally, population projections are often used as a base for constructing other types of projections. For example, population projections can be used for school enrollment projections by applying enrollment rates to the appropriate age groups. They can be used for labor force projections by applying labor force participation rates to the appropriate age, sex, racial, or ethnic groups. They can be used for projecting the number of births by applying birth rates to the projected female population. Analyses based directly or indirectly on population projections provide the basis for many types of decision making in both the public and private sectors. As a practical matter, this may be the most important use of population projections.

1.2.2 Projections and Decision Making

Population projections are interesting to demographers because they reveal a great deal about the components of growth, the momentum of population change, and the implications of particular assumptions. To most non-demographers, however, these issues are—at best—only mildly interesting. The primary value of population projections to most data users is how they can be used to improve real-world decision making. The following examples illustrate some of the uses of population projections.

1.2.2.1 Will Texas Run Out of Water?

Texas is a rapidly growing state drawing its water from aquifers, lakes, and rivers. These sources are replenished over time through rainfall. But rainfall in Texas is wildly variable over time and space, with averages ranging from over 40 in. per year in the eastern part of the state to fewer than 10 in. in the western part. Agriculture and industry are the major users of water, but households are important as well. Population growth affects the demand for water directly through household formation and size and indirectly through its impact on the demand for agricultural and industrial output. In 2012, the State of Texas published a 50-year state water plan (Texas Water Development Board 2012). Population and household projections for counties and subcounty areas played an important role in the development of that plan.

1.2.2.2 Where Should Encinitas Put Its New Fire Stations?

Encinitas is coastal city in southern California. Local officials were concerned about the city's ability to respond to future demands for fire protection, and contacted the San Diego Association of Governments (SANDAG) for assistance in determining how many stations were needed and where they should be located. SANDAG developed a plan based on the projected number and location of households, road networks, travel times, access to "critical sites" (e.g., hospitals, schools, nursing homes), and land use plans. Population and household projections at the block level were used for constructing this plan (Tayman et al. 1994).

1.2.2.3 Does Hillsboro Need a New School?

Hillsboro is a suburb of Portland, Oregon. In the mid-1990s, the city had 20 elementary schools, four middle schools, and three high schools, with a total of nearly 16,500 students (Swanson et al. 1998). The school board faced a formidable planning task because of rapid population growth and the pending unification of separate elementary, middle, and high school districts. They contracted with a group of consultants to study how to combine the current districts, determine whether any new schools were needed, and develop attendance zones for each school. The consultants developed a plan based on population projections by age, sex, race, ethnicity, and income by traffic analysis zone. [Traffic analysis zones are small, user-designed areas developed for transportation planning; they are typically composed of one or more blocks]. These projections were then aggregated to form projections for each attendance zone within the newly formed school district.

1.2.2.4 Can Hospital X Support a New Obstetrical Unit?

Hospital X is located in the central city of a medium-sized metropolitan area in the southeastern United States. Seeking to establish an obstetrical unit in a suburban satellite hospital, the administrators of Hospital X applied to the local health planning board for approval. The approval process required that Hospital X demonstrate the need for additional maternity services in the area. The application was opposed by a nearby suburban hospital which already offered maternity services. The opposing hospital retained a demographic consultant to determine if additional maternity services were actually needed. The critical factor in the case was the number of births projected for the satellite hospital's service area. The consultant used population projections by age and sex and assumptions regarding future birth rates to demonstrate that the projected increase in births was insufficient to justify the establishment of a new obstetrical unit (Thomas 1994).

1.2.2.5 What Does Population Growth Mean for Land Use in Dublin?

Dublin is a small but rapidly growing city in central Ohio. Its population was less than 4,000 in 1980 but quadrupled by 1990 and nearly doubled again by 2000. Its residents were concerned about dealing with the impact of additional future growth.

Planners developed three series of population projections based on low, medium, and high growth assumptions and traced out the implications of those projections for residential, recreational, employment, and other types of land use (Klosterman 2007). These projections helped the city develop public policies affecting further population and employment growth.

1.2.3 Forecasting and Planning

Any plan for the future must be based—at least in part—on a projection (or forecast). Even the most mundane activities of everyday life illustrate this point. When one walks out the door in the morning and decides whether to take along an umbrella, one is forecasting the likelihood of rain that day. A household's saving decisions, a corporation's investment decisions, a state government's spending decisions, a local government's road-building decisions, and a school board's hiring decisions all reflect plans based implicitly or explicitly on forecasts. The examples described above show how population projections affect plans developed by a variety of businesses and government agencies. Forecasting and planning are closely intertwined.

They are not synonymous, however. Each has its own goals and objectives. Forecasting attempts to *predict* the future, whereas planning seeks to *affect* it. Isserman (1984) discussed three types of forecasts. *Pure* forecasts describe the most likely future in the absence of intervention; *contingency* forecasts describe possible futures under different assumptions; and *normative* forecasts describe the desired future. These terms reflect the different roles played by projections. Since the objective of planning is to affect the future, successful planning may render a forecast obsolete and inaccurate; that is, active intervention may cause future population trends to deviate from the paths they would have followed in the absence of intervention. Consequently, there may be a fundamental conflict between planning and forecasting.

In addition, projections themselves may affect future growth. For example, areas projected to grow rapidly may do so in part because the predicted growth attracts job seekers and businesses wishing to relocate or expand. Areas projected to decline may do so in part because businesses and workers are driven away by their apparently poor prospects. In these circumstances, population forecasts influence the very trends they seek to predict, perhaps even becoming self-fulfilling prophecies (Isserman and Fisher 1984; Moen 1984). Planners may influence population growth through their forecasts as well as their plans.

Government planners use a variety of tools to influence the pace, distribution, and characteristics of population growth. Some local governments try to spur growth by actively courting new businesses, reducing tax rates, extending infrastructure into new areas, or improving the quality of government services. Others attempt to restrict growth by setting limits on the number of residential building permits issued, denying water and sewer services, instituting impact fees on new structures, banning certain types of industries, or limiting the number of unrelated persons living in one household. State governments influence population growth through policies affecting the economic environment, the cost of living, and the quality of services.

Forecasting and planning are distinct but closely related activities. Particularly at the local level, they are political in nature and require the balancing of differing interests and viewpoints from a variety of stakeholders. Successful forecasting and planning inform the policy-making process by presenting a variety of realistic scenarios, facilitating community understanding, and preparing the public for dealing with an uncertain future (Klosterman 2007; Smith 2007; Tayman 1996). They not only react to projected population changes, but seek to influence those changes as well. When public policy influences population growth, forecasting and planning cannot be separated.

1.3 How Can This Book Help?

A great deal has been written about population projections. One branch of the literature has addressed projection methodology (Booth 2006; Davis 1995; Pittenger 1976; Siegel 2002; Wilson and Rees 2005). Another has focused on analysis and evaluation, with a particular emphasis on forecast accuracy (Chi 2009; Keilman 1990; Long 1995; Rayer 2008; Smith and Sincich 1992; Stoto 1983). We cover both branches in this book. We describe and illustrate the most commonly used projection methods, with an emphasis on problems unique to applications for small areas. We also discuss the determinants of population growth, quality of data sources, formation of assumptions, development of evaluation criteria, and determinants of forecast accuracy. Our aim is to provide the reader with an understanding not only of the mechanics of common projection methods, but also of the complex analytical issues that make population forecasting an art as well as a science. Box 1.2 lists some of the major producers of state and local projections.

1.3.1 Objectives

We have three fundamental objectives in writing this book: to describe commonly used projection methods, to analyze their strengths and weaknesses, and to provide practical guidance to analysts called upon to produce population projections or use them for decision-making purposes.

Box 1.2 Who Makes State and Local Population Projections?

Federal government—The Census Bureau published its first set of state population projections in 1952 and published several sets each decade through the 1990s. It released an interim set of state projections in 2005 but has not produced any additional sets since that time. Current plans call for a new set of state projections by 2015. The Census Bureau produced a set of projections for metropolitan areas in 1969 but has not made any other projections below the state level. The Bureau of Economic Analysis made several sets of population projections for states, economic areas, and metropolitan areas in the 1970s, 1980s, and 1990s, but has made no projections since 1995.

State demographers—Most state governments designate an agency to produce "official" population projections. These agencies are often part of state government but are sometimes part of a university. Most states make projections at the state and county levels; a few also make projections for selected subcounty areas. Most states make projections by age, sex, and race; a few also make projections by Hispanic origin. Representatives from each state and the Census Bureau formed the Federal-State Cooperative Program for Population Projections (FSCPP) in 1981. This organization promotes the development and testing of projection methods; encourages the collection and exchange of reliable data; and provides a forum for sharing data, information, and ideas.

Local government agencies—Agencies such as city and county planning departments and associations (or councils) of governments often make population projections for subcounty areas such as census tracts, block groups, ZIP code areas, and traffic analysis zones. The level of geographic and demographic detail varies from place to place.

Private vendors—A number of private data companies make population projections for states, counties, and subcounty areas such as census tracts, block groups, ZIP code areas, and a variety of customized geographic areas. These projections often contain a high level of geographic and demographic detail. They are produced on a regular schedule and are sold to data users in the public and private sectors.

Other private businesses—Some business enterprises have staff members who produce population projections for use within the company. Demographic consultants also produce a variety of customized projections under contract with individual clients. These projections are often proprietary and are not generally available for public use.

Note: In 1999, the U.S. Bureau of the Census officially changed its name to the U.S. Census Bureau. For simplicity, we refer to this agency simply as the Census Bureau.

1.3.1.1 Describing Projection Methods

First, we describe a variety of population projection methods. Some are simple, others much more complex. We use non-technical language whenever possible and supplement the discussion with illustrations and step-by-step examples. We include equations where they illuminate the discussion, but try not to overwhelm the reader with mathematics. For complex methods, of course, the discussion necessarily becomes more technical. We emphasize methods that most demographers, planners, market researchers, and other analysts will be able to use for state and local projections. We provide step-by-step illustrations of the cohort-component method and most of the trend extrapolation techniques, but do not provide detailed illustrations for time series, structural, or microsimulation models or for the most data-intensive applications of the cohort-component method (e.g., parameterized multi-state models). Interested readers may consult the reference works cited for further information on these methods.

1.3.1.2 Analyzing Strengths and Weaknesses

Simply knowing the mechanics of various methods is not enough; one must also be aware of each method's strengths and weaknesses. Otherwise, the analyst will be unable to choose the method (or methods) that are best suited for a given set of projections. Our second objective, then, is to develop a set of criteria for evaluating the strengths and weaknesses of each projection method and show how to use those criteria to evaluate the methods described in this book.

Each method has a specific combination of characteristics. Some have large data requirements, others have small requirements. Some provide a great deal of demographic detail, others provide little. Some are time consuming and costly to apply, others are quick and inexpensive. Some require a high level of modeling and statistical skills, others require only simple skills. Some are easy to explain to data users, others are difficult to explain. For any given purpose, then, some methods are more useful than others. Only after considering the strengths and weaknesses of each method can the analyst choose the one(s) best suited for a particular project.

Because population projections are so widely used as forecasts of future population change, we examine forecast accuracy in detail, evaluating differences by projection method, population size, growth rate, length of base period, length of projection horizon, and launch year. We believe this discussion will help the analyst choose the best method(s) for any particular purpose and provide a basis for judging the uncertainty inherent in population projections.

1.3.1.3 Providing Practical Guidance

Our most fundamental objective is to provide practical guidance to demographers, planners, market researchers, and others called upon to produce state and local population projections or to use projections for decision-making purposes. Describing alternative methods and discussing their strengths and weaknesses is necessary but not sufficient for achieving this goal. One must also consider the context in which projections are made. What theoretical models and data sources are most appropriate for a particular type of projection? What social, economic, cultural, and political factors might affect the choice of assumptions? What special circumstances must be considered? Are any adjustments to the models or data necessary? If so, how can they be made? What potential pitfalls should the analyst watch out for? We provide answers to these questions throughout the book.

This book will not answer every question, of course, but we believe it will help the producers of population projections focus on the relevant issues, collect the necessary data, develop and apply appropriate models, interpret results, and evaluate the trade-offs that must be made when demands are seemingly unlimited but resources are not. Similarly, it will help users of population projections ask the right questions and evaluate the quality of the answers they receive. Providing practical guidance is the most important objective of this book.

1.3.2 Geographic Focus

Much of the research on population projections has focused on projections at the national level (Bongaarts and Bulatao 2000; Cohen 1986; Hyndman and Booth 2008; Keyfitz 1981; Lee and Tuljapurkar 1994; Shang 2012; Stoto 1983). Although this research has been very valuable, conclusions based on studies of national projections are not always applicable to states and local areas. There are several reasons why this might be true.

First, there are substantial differences in data availability and reliability between national and subnational areas. Some data series are available only at the national level. Others are available with greater frequency at the national level than at state and local levels. Due to reporting, coverage, and sampling errors, data quality is likely to be better for nations than for subnational areas (especially for small areas). Consequently, certain projection methods that work well at the national level may not work well (or work at all) at the state and local levels.

Second, migration—both international and domestic—plays a greater role in population growth at the state and local levels than at the national level. Fertility and mortality are the major determinants of population growth in most countries, with international migration having a relatively small impact. Although international migration has a larger impact on population growth in the United States than in most countries, it still accounts for just over one-third of the nation's annual population growth and is relatively stable from year to year. In contrast, migration is the primary determinant of population change in many states and local areas and is much more volatile over time than either fertility or mortality. This volatility makes migration more difficult to forecast accurately, adding a major source of uncertainty to subnational projections that is small or non-existent in most national projections.

Finally, the small size of many local areas means that individual events have a greater impact on population change than is the case for nations (and most states). Examples include the construction of a prison, the growth of a college or university, the opening of a new highway, and the closing of a major employer. Factors like these cause population growth to be more volatile and unpredictable for small areas than large areas. By *small areas*, we mean counties and subcounty areas such as cities, townships, school districts, census tracts, and traffic analysis zones.

We believe an emphasis on states and local areas is justified by their unique characteristics, by the relatively small amount of research that has been done at the subnational level, and by the widespread use of small-area projections for decision-making purposes. This emphasis means we pay special attention to problems of data availability and reliability, the role of migration, and the impact of special events and unique circumstances on population growth. However, except for urban systems models, all the methods described in this book can be used for national projections as well as for state and local projections.

We focus on data sources and geographic areas in the United States—the country we know best—but much of our discussion is relevant for subnational projections in other countries with regularly conducted censuses, good vital registration systems, and a wide range of administrative records. For countries just developing these data resources, the discussion will provide a point of departure but not a complete road map to the construction of population projections.

1.3.3 Coverage

This book is composed of four parts. Chapters 1 and 2 provide a general introduction to the book's topics and terminology. Chapter 1 discusses the reasons for making projections, defines some basic concepts, and describes the scope of the book. Box 1.3 defines some of basic terms used throughout the book. Chapter 2 is a primer on population analysis, covering additional demographic concepts and terminology. This chapter will be review material and can be skipped by readers with training in demography, but will be helpful to newcomers to the field.

Chapters 3, 4, 5, 6 and 7 focus on the cohort-component method. Chapter 3 provides an overview of the method, including a brief history of its development and use. Chapter 4 discusses the mortality component, covering the calculation of several mortality measures, sources of data, the construction of survival rates, alternative approaches to projecting survival rates, and some examples of mortality projections for states and local areas. Chapter 5 discusses the fertility component, covering the calculation of several fertility measures, sources of data, a description of the cohort and period perspectives, alternative approaches to projecting fertility rates, and some examples of fertility projections for states and local areas. Chapter 6 discusses the migration component, covering a number of migration definitions and measures, sources of data, the determinants of migration, alternative approaches to projecting migration, and several critical issues related to migration projections for states and local areas. Chapter 7 provides several step-by-step examples showing

Box 1.3 Some Basic Terminology

Projection: The numerical outcome of a particular set of assumptions regarding future population trends.

Forecast: The projection deemed most likely to provide an accurate prediction of the future population.

Estimate: A calculation of a current or past population, typically based on symptomatic indicators of population change.

Base year: The year of the earliest data used to make a projection.

Launch year: The year of the latest data used to make a projection.

Target year: The year for which the population is projected.

Base period: The interval between the base year and the launch year.

Projection horizon: The interval between the launch year and a target year.

Projection interval: The increments in which projections are made.

For example, if data from 2000 through 2010 are used to project the population in 2020, then 2000 is the base year; 2010, the launch year; 2020, the target year; 2000–2010, the base period; and 2010–2020, the projection horizon. These projections would be made in 10-year intervals.

how to apply the cohort-component method and discusses some of its strengths and weaknesses.

Chapters 8, 9, 10, and 11 discuss other approaches to projecting state and local populations. Chapter 8 covers trend extrapolation methods, including a brief history of their application, a description of the most commonly used methods, examples of each method, and an assessment of their strengths and weaknesses. Chapter 9 covers economic-demographic and urban systems models—the two main types of structural models used for state and local projections—and microsimulation. This chapter discusses some of the theory underlying these models, gives examples of how they can be used, and evaluates their strengths and weaknesses. Chapter 10 discusses several special circumstances that may be encountered when making population projections and suggests some ways for dealing with them. Chapter 11 describes methods that can be used for projecting population-related variables such as households, school enrollment, health characteristics, and the labor force.

The last part of the book focuses on evaluation and analysis. Chapter 12 describes several criteria for evaluating projections and compares the methods discussed in this book according to these criteria. Chapter 13 analyzes forecast accuracy and bias, covering alternative error measures, factors affecting accuracy and bias, the potential for combining projections, and ways to account for uncertainty. These two chapters will help readers judge the validity of population projections and determine how useful they are likely to be for decision-making purposes. Chapter 14 summarizes many of the points made throughout the book and provides practical guidance for making small areas projections. Finally, the Epilogue speculates on where the field of population projections may be headed.

1.3.4 Target Audience

This book is aimed primarily at two groups of readers. The first consists of analysts working for state and local governments, private businesses, universities, and non-profit organizations who are responsible for making population projections for states and local areas. This group not only includes demographers, but also land use planners, transportation planners, environmental planners, school district administrators, market analysts, personnel managers, retirement benefits administrators, and sales forecasters. We believe this book gives practitioners the tools they need to decide which data sources to use, which methods to apply, how best to apply them, and what problems to watch out for. It also gives the users of population projections the tools they need to evaluate the validity of the projections they are using.

The second group is comprised of students in courses dealing with demographic methods or state, regional, and local planning. We believe the book will be useful as the primary textbook in courses focusing on population projections and as supplementary reading for courses in which population projections are covered in a short module. The book is not highly mathematical, but it assumes that readers have at least a basic knowledge of mathematics and statistics. We believe it is suitable for both graduate students and upper-level undergraduate students.

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Chapter 2
Fundamentals of Population Analysis

Demography is defined as the scientific study of population. Although it typically focuses on the human population, many of its concepts, measures, and techniques can be extended to non-human populations as well. It covers five basic topics:

1. The size of the population.
2. Its distribution across geographic areas.
3. Its composition (e.g., age, sex, race, and other characteristics).
4. Changes in population size, distribution, and composition over time.
5. The determinants and consequences of population growth.

In this chapter, we focus on the first four of these topics. We describe a number of basic demographic concepts, define a number of commonly used terms, and discuss several sources of demographic data. Our objective is to give readers with little training or experience in formal demography a brief introduction to the field. More comprehensive discussions can be found in Newell (1988), Poston and Micklin (2005), Rowland (2011), Siegel and Swanson (2004), and Weeks (2012).

2.1 Demographic Concepts

2.1.1 Size

The most basic demographic concept is population size. Typically, *population size* refers to the number of people residing in a specific area at a specific time. For example, California had a population of 37,253,956 on April 1, 2010, whereas Wyoming had a population of 563,626 (see Table 2.1). These were the largest and smallest states in the United States, in terms of population size.

Population size is seemingly a simple concept, but there is some ambiguity regarding how it is measured. Americans are a very mobile population, and many people spend part of their time in one place and part in another (e.g., at home, at

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Table 2.1 Population change for states, 2000–2010

	2000	2010	Change	
			Numeric[a]	Percent[b]
Northeast				
Connecticut	3,405,650	3,574,097	168,447	4.9
Maine	1,274,779	1,328,361	53,582	4.2
Massachusetts	6,349,364	6,547,629	198,265	3.1
New Hampshire	1,235,807	1,316,470	80,663	6.5
New Jersey	8,414,764	8,791,894	377,130	4.5
New York	18,977,026	19,378,102	401,076	2.1
Pennsylvania	12,280,548	12,702,379	421,831	3.4
Rhode Island	1,048,259	1,052,567	4,308	0.4
Vermont	608,613	625,741	17,128	2.8
Midwest				
Illinois	12,419,927	12,830,632	410,705	3.3
Indiana	6,080,827	6,483,802	402,975	6.6
Iowa	2,926,538	3,046,355	119,817	4.1
Kansas	2,688,925	2,853,118	164,193	6.1
Michigan	9,938,823	9,883,640	−55,183	−0.6
Minnesota	4,919,631	5,303,925	384,294	7.8
Missouri	5,596,564	5,988,927	392,363	7.0
Nebraska	1,711,230	1,826,341	115,111	6.7
North Dakota	642,237	672,591	30,354	4.7
Ohio	11,353,336	11,536,504	183,168	1.6
South Dakota	754,858	814,180	59,322	7.9
Wisconsin	5,363,757	5,686,986	323,229	6.0
South				
Alabama	4,447,207	4,779,736	332,529	7.5
Arkansas	2,673,293	2,915,918	242,625	9.1
Delaware	783,559	897,934	114,375	14.6
District of Columbia	572,086	601,723	29,637	5.2
Florida	15,982,571	18,801,310	2,818,739	17.6
Georgia	8,186,653	9,687,653	1,501,000	18.3
Kentucky	4,042,193	4,339,367	297,174	7.4
Louisiana	4,469,035	4,533,372	64,337	1.4
Maryland	5,296,647	5,773,552	476,905	9.0
Mississippi	2,844,754	2,967,297	122,543	4.3
North Carolina	8,046,346	9,535,483	1,489,137	18.5
Oklahoma	3,450,451	3,751,351	300,900	8.7
South Carolina	4,012,023	4,625,364	613,341	15.3
Tennessee	5,689,427	6,346,105	656,678	11.5
Texas	20,851,820	25,145,561	4,293,741	20.6
Virginia	7,079,057	8,001,024	921,967	13.0
West Virginia	1,808,193	1,852,994	44,801	2.5

(continued)

Table 2.1 (continued)

	2000	2010	Change	
			Numeric[a]	Percent[b]
West				
Alaska	626,933	710,231	83,298	13.3
Arizona	5,130,247	6,392,017	1,261,770	24.6
California	33,871,653	37,253,956	3,382,303	10.0
Colorado	4,302,086	5,029,196	727,110	16.9
Hawaii	1,211,497	1,360,301	148,804	12.3
Idaho	1,293,957	1,567,582	273,625	21.1
Montana	902,200	989,415	87,215	9.7
Nevada	1,998,250	2,700,551	702,301	35.1
New Mexico	1,819,017	2,059,179	240,162	13.2
Oregon	3,421,524	3,831,074	409,550	12.0
Utah	2,233,183	2,763,885	530,702	23.8
Washington	5,894,281	6,724,540	830,259	14.1
Wyoming	493,786	563,626	69,840	14.1
United States	281,426,600	308,747,548	27,320,938	9.7

Sources: U.S. Census Bureau, 2000 and 2010 censuses
[a]2010 population − 2000 population
[b]Population change / 2000 population × 100

work, on vacation, or on a business trip). Where should these people be counted when a census is conducted?

There are two basic approaches to answering this question. The *de facto* approach counts people where they are physically located on census day, regardless of how much time they spend at that location. Under this approach, all tourists, business travelers, and seasonal residents present in Phoenix on census day are counted as Phoenix residents, along with the usual residents of Phoenix who are in town that day. Usual residents who are out of town on census day, however, are not counted as Phoenix residents. The *de jure* approach counts people at their usual (or permanent) place of residence, regardless of where they are physically located on census day. Under this approach, tourists, business travelers, and other visitors temporarily present in Phoenix on census day are counted as residents of Chicago, Omaha, or any other place in which they normally reside. The first approach is used in many countries lacking well-developed statistical systems. The second approach is used in the United States, Canada, and most other industrialized countries and is the approach we follow in this book.

The *de jure* approach means that many people physically present in an area at one time or another are omitted from population counts, estimates, and projections. These omissions may be substantial for some places. For example, it was estimated that Florida had more than 1.2 million temporary residents spending at least 1 month in the state during the winter of 2005 (Smith and House 2007); these people were not included in Florida's official population estimates and projections. The Census Bureau has established guidelines for determining place of residence for population subgroups such as military personnel, college students, migrant farmworkers, snowbirds, business travelers, and the homeless (Cork and Voss

2006). In spite of these guidelines, there is still a substantial amount of ambiguity concerning who should or should not be included in official population statistics. Chapter 6 provides a more detailed discussion of these issues.

Populations need not refer to geographic areas. For example, a population could refer to all the employees of a company or all the enrollees in a healthcare plan. Demographic analyses can be performed for populations defined for these entities as well as for populations defined for geographic areas. In this book, however, we focus primarily on populations defined for specific geographic areas.

2.1.2 Distribution

The *distribution* of a population refers to its geographic location. There are several ways to define geographic areas. The most fundamental is the set of geographic areas developed for statistical purposes such as collecting and reporting demographic data in the decennial census (U.S. Census Bureau 2011). The boundaries for these areas are determined by the Census Bureau, in consultation with local government agencies and user groups. These areas form the building blocks used in constructing data sets for other types of geographic areas.

The most important geographic areas defined for statistical purposes are blocks, block groups, and census tracts. *Blocks* are geographic areas bounded on all sides by visible features such as streets or railroad tracks or by invisible boundaries such as city or township limits. They are the smallest geographic units for which data are tabulated. *Block groups* are clusters of blocks and generally contain between 600 and 3,000 residents. They do not cross state, county, or census tract boundaries but may cross other types of boundaries. *Census tracts* are relatively permanent areas designed to be homogeneous with respect to population characteristics, living conditions, and economic status. They generally contain between 1,200 and 8,000 residents and do not cross state or county boundaries but may cross other types of boundaries.

Geographic areas can also be defined according to administrative or political criteria. Examples include states, counties, cities, townships, congressional districts, school districts, and water management districts. For many purposes these are the most important types of geographic areas that can be defined. They play an important role in planning, budgeting, and political representation and are often used for analyzing population growth and demographic change. However, geographic areas defined according to administrative or political criteria have several limitations. Their boundaries are somewhat arbitrary and do not account for important economic, cultural, social, or geographic factors. In addition, some of these boundaries change over time, making it difficult (or impossible) to conduct time series analyses.

Geographic boundaries can also be defined according to other criteria. The U.S. Postal Service defines ZIP code areas for purposes of delivering the mail. Businesses define service areas to identify the location of their customers or clients. Local planners define traffic analysis zones for developing transportation plans.

Population data pertaining to these geographic areas are typically based on data collected or estimated for the statistical and administrative/political areas described above. Clearly, a wide variety of geographic areas can be used when analyzing the distribution of the population.

2.1.3 Composition

Composition refers to the characteristics of the population. For population projections, the most commonly used characteristics are age, sex, race, and ethnicity. These are the characteristics we refer to most frequently in this book.

Age is perhaps the most important demographic characteristic because it has such a large impact on so many aspects of life, for individuals as well as for society as a whole. The age structure of a population affects its birth rate, death rate, and crime rate. It affects the demand for public education, healthcare, and nursing home care. It affects the housing market, the labor market, and the marriage market. It has tremendous implications for Social Security, Medicare, and private pension systems. No other characteristic is more valuable for a wide variety of planning and analytical purposes than age composition.

Sex composition is also important for many purposes. In fact, these two characteristics are often combined to reflect the age-sex structure of the population (Weeks 2012, p. 309). We use the term *sex* to refer to the strictly biological differences between males and females; *gender* refers to non-biological differences related to social, cultural, political, and economic factors.

The age-sex structure is often illustrated using *population pyramids*. Population pyramids are graphic representations showing the number (or proportion) of the population in each age-sex group. For countries, the shape of a pyramid is determined primarily by the population's fertility history. For states and local areas, migration plays an important role as well. A pyramid with a wide base reflects a young population.

Population pyramids tell a great deal about a population. Consider Fig. 2.1, which shows pyramids for the U.S. population in 1960 and 2010. Both populations have more males than females in the youngest age groups. This reflects the larger number of male births, a worldwide phenomenon (typically, there are about 105 male births for every 100 female births). In the middle and especially the older age groups, however, both populations have more females than males. This reflects the lower mortality rates of females than males, also a widespread phenomenon. The impact of the baby boom—people born between 1946 and 1964—is clearly evident, with large numbers of children in 1960 and large numbers of people in their 40s, 50s, and 60s in 2010.

Race and ethnicity are two other widely used demographic characteristics. Since 1997, the Office of Management and Budget (OMB) has required federal agencies to use a minimum of five racial categories: White; Black or African American; American Indian or Alaska Native; Asian; and Native Hawaiian or Other Pacific

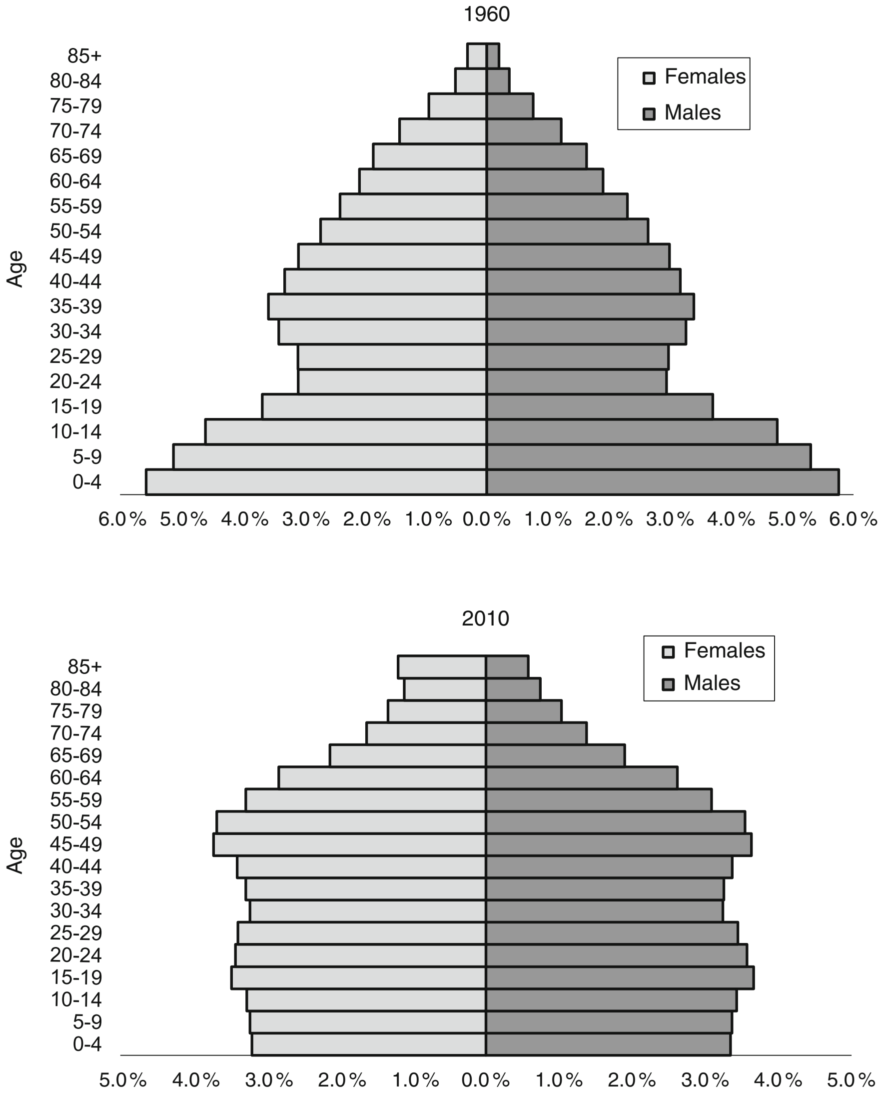

Fig. 2.1 Population pyramids for the United States, 1960 and 2010 (Source: U.S. Census Bureau, 1960 and 2010 censuses)

Islander (Humes et al. 2011). More detailed categories based on ethnicity and national origin also can be used (e.g., Chinese, Filipino, and Samoan). In addition, the population is often classified as Hispanic or non-Hispanic. It should be noted that "Hispanic" is an ethnic category, not a racial category; consequently, people are classified both by race and by Hispanic origin.

The 2000 census introduced an important change in the collection of racial data. For the first time, respondents were allowed to list themselves as belonging to more than one racial category; prior to that time, they could list only a single category. The 2000 census thus included a large number of potential multi-race combinations, in addition to the five single-race categories. This change has been controversial, creating uncertainty regarding the interpretation and use of racial data and the consistency of those data over time. In the United States, 2.4% of the population was classified as belonging to more than one racial group in 2000 and 2.9% in 2010 (Humes et al. 2011). However, this proportion varies substantially from place to place. For example, 23.6% of the population of Hawaii was classified as belonging to more than one racial group in 2010, compared to only 1.1% of the population of Mississippi (U.S. Census Bureau 2012b).

Composition also refers to characteristics such as marital status, household relationship, employment status, income, education, and occupation. We discuss methods for projecting several of these characteristics in Chap. 11.

2.1.4 Change

Population *change* is measured as the difference in population size between two points in time (i.e., two specific dates). A point in time can correspond to the date of a census or a population estimate. Since censuses are typically more accurate than estimates, measures of change based on censuses are generally more accurate than measures based on estimates.

Population change can be expressed in either numeric or percentage terms, as shown in Table 2.1. Numeric change is computed by subtracting the population at the earlier date from the population at the later date. A negative sign indicates a population loss. Percent change is computed by dividing the numeric change by the population at the earlier date and multiplying by 100. For example, Texas had a population of 20,851,820 on April 1, 2000 and a population of 25,145,561 on April 1, 2010, yielding:

$$\text{Numeric change}: 25{,}145{,}561 - 20{,}851{,}820 = 4{,}293{,}741$$
$$\text{Percent change}: (4{,}293{,}741/20{,}851{,}820)\,(100) = 20.6\%$$

Texas had the largest numeric population change of any state between 2000 and 2010, but Nevada had the largest percent change (35.1%). Michigan was the only state to lose population during the decade.

Population change can also be expressed in terms of an average annual numeric change (AANC), which can be computed by dividing total change by the number of years between the two dates:

$$\text{AANC} = (\text{P}_\text{l} - \text{P}_\text{b})/\text{y}$$

where P_l is the population at the later date, P_b is the population at the earlier date, and y is the number of years between the two. In Texas, for example, the population grew by an average of 429,374 per year between 2000 and 2010:

$$\mathrm{AANC} = (25{,}145{,}561 - 20{,}851{,}820)/10 = 429{,}374$$

For some purposes it is helpful to express annual population change in relative rather than numeric terms, or as annual percent changes (i.e., growth rates) rather than as annual numeric changes. Average annual growth rates can be calculated in two slightly different ways. The first is based on a geometric model:

$$\mathrm{r} = (\mathrm{P_l}/\mathrm{P_b})^{(1/\mathrm{y})} - 1$$

where r is average annual geometric growth rate and the other terms are defined as before. Again, using Texas as an example:

$$\mathrm{r} = (25{,}145{,}561/20{,}851{,}820)^{(1/10)} - 1 = .0189, \text{or } 1.89\% \text{ per year}$$

The geometric growth rate calculated in this manner is based on compounding in discrete intervals (i.e., at specific dates). In this example, growth is compounded once a year. Since population growth occurs continuously, it may be useful to use an exponential model based on continuous compounding:

$$\mathrm{r} = [\ln\,(\mathrm{P_l}/\mathrm{P_b})]/\mathrm{y}$$

where r is the average annual exponential growth rate and ln is the natural logarithm. For Texas, the average annual exponential growth rate is calculated as:

$$\mathrm{r} = [\ln\,(25{,}145{,}561/20{,}851{,}820)]/10 = 0.0187, \text{or } 1.87\% \text{ per year}$$

Geometric and exponential growth rates are generally about the same. Geometric rates are always slightly larger than exponential rates because they are calculated at discrete intervals rather than continuously. The more rapidly growing the area, the greater the difference between geometric and exponential growth rates.

The measures of population change described above are simple and straightforward. However, they are not always easy to implement properly because of changes in geographic boundaries, changes in the accuracy of the base data, or changes in definitions.

The geographic boundaries of states have been constant for a long time. The same has been true for most counties, at least for the last several decades. Many cities, metropolitan areas, block groups, voting districts, and ZIP code areas, however, have experienced sudden (and sometimes large) boundary changes. Although the Census Bureau attempts to hold census tract boundaries constant from one decennial census to another (except for subdivisions into coterminous sets of smaller tracts), changes at other levels of census geography occur frequently. Analysts must be aware of changes in geographic boundaries and make adjustments when necessary. Consistent measures of population change are possible only if geographic boundaries are held constant over time.

Changes in the accuracy of the base data also affect the measurement of population change. For example, suppose that a city's population was counted as 10,000 in 2000 and 11,000 in 2010, but that it was later discovered that the 2010 census had missed an apartment complex with 1,000 residents. The population change based on the corrected numbers (2,000) would be twice as large as the change based on the uncorrected numbers (1,000). Population estimates are typically less accurate than population counts; consequently, they introduce an additional source of error. It is often difficult to uncover and correct errors in the underlying data, but in some places those errors have a substantial impact on calculations of population change.

Changes in the definition or interpretation of demographic concepts can also affect the measurement of change. Take race, for example. Respondents were allowed to list only one racial category in the 1990 census but could list multiple categories in 2000. This change in reporting practices may have contributed to some unusual estimates of population change (e.g., the large increase in the number of American Indians between 1990 and 2000). Problems of definition and interpretation are particularly significant in censuses based on self-enumeration, such as those in the United States and Canada. Although guidelines for answering questions are provided, they are not followed in the same way by all respondents. Problems of definition and interpretation potentially affect every type of data collected in a census or survey, from the number of persons in a household to their detailed characteristics.

Measures of population change always refer to a specific population and a specific period of time; in most instances, they refer to a specific geographic area as well. Population change can also be measured for various subgroups of the population (e.g., females, Asians, and teenagers), different geographic areas (e.g., counties and cities), and different time periods (e.g., 1990–2000 and 2000–2010). In other words, *population change* can refer to changes in size, distribution, or composition, or to any combination of the three.

2.2 Components of Change

There are only three components of population change: births, deaths, and migration. A population grows through the addition of births and in-migrants, and declines through the subtraction of deaths and out-migrants. Understanding these three demographic processes is essential to understanding the nature and causes of population change.

2.2.1 Mortality

Mortality is the process by which deaths occur in a population. Changes in mortality rates are determined primarily by changes in living conditions and advances in medicine, public health, and science. Low-income countries typically have higher mortality rates than high-income countries; within countries, low-income people typically have higher mortality rates than high-income people. Education also has a substantial impact on mortality rates, even when differences in income are accounted for.

Mortality rates have declined tremendously over the last two centuries in Europe, North America, and other high-income countries. They have also declined dramatically in many lower-income countries, primarily over the last 60 years. There is more variability in mortality rates within low- and middle-income countries than within high-income countries, but even high-income countries may display substantial differences among various racial, ethnic, and socioeconomic groups. Chapter 4 discusses several mortality measures, sources of data, alternative viewpoints regarding future mortality trends, and several ways to implement the mortality component of population projections.

2.2.2 Fertility

Fertility is the occurrence of a live birth (or births). It is determined by a variety of biological, social, economic, psychological, and cultural factors. Biological factors determine the physiological capacity to reproduce and socioeconomic and personal factors determine perceptions of the costs and benefits of children. The availability and effectiveness of contraceptives also plays a role, affecting the ability to control the number and timing of births.

Fertility rates have declined dramatically over the last two centuries in Europe, North America, and other high-income countries. Causes of this decline have included higher costs and lower economic benefits of children, lower rates of infant and child mortality, changes in female roles in the home and society, and improvements in contraceptive efficiency. Fertility rates have declined significantly in recent decades in many low- and middle-income countries as well, especially in Asia and Latin America. In many African and Middle Eastern countries, however, rates remain very high.

Although fertility rates are low (sometimes very low) in high-income countries, there is often a substantial degree of variation from place to place and from one racial, ethnic, or socioeconomic group to another. This is especially true in the United States, which has a heterogeneous population and covers a vast geographic area. Chapter 5 discusses several fertility measures, sources of data, several theories of the determinants of fertility, and a variety of ways to implement the fertility component of cohort-component projections.

2.2.3 Migration

Migration is the process of changing one's place of residence from one geographic area to another. It typically refers solely to changes in place of usual residence, thereby excluding all short-term or temporary movements such as commuting to work, visiting friends or relatives, going away on vacation, and taking business trips. Migration is often distinguished from *local mobility*, which refers to changes of address within a particular community or geographic area. At the aggregate level, factors affecting migration include area-specific characteristics such as wage rates, unemployment rates, costs of living, and amenities (e.g., climate and recreational opportunities). At the individual level, migration is also affected by a host of personal characteristics such as age, education, occupation, and marital status.

The migration literature uses a number of descriptive terms. *Gross migration* refers to the total number of migrants into or out of an area (e.g., 600 in-migrants and 400 out-migrants). *Net migration* refers to the difference between the two (e.g., a net increase of 200). *Domestic (or internal) migration* refers to changes in residence from one place to another within the same country. *Foreign (*or *international) migration* refers to changes in residence from one country to another.

International migration is a minor component of population growth in many countries but not in the United States, where it constitutes a large and increasing proportion of growth. It is at the subnational level, however, that migration attains its greatest importance. Migration levels vary tremendously from one place to another in the United States and—for any given place—are subject to large, sudden changes over time. Migration affects not only the total population of an area, but its age, sex, race, income, education, and other characteristics as well. Chapter 6 discusses several migration definitions and measures, sources of data, the determinants of migration, and alternative approaches to projecting migration.

2.2.4 Demographic Balancing Equation

The overall growth or decline of a population is determined by the interplay among the processes of mortality, fertility, and migration. The nature of this interplay is formalized in the demographic balancing equation:

$$\mathrm{P_l - P_b = B - D + IM - OM}$$

where P_l is the population at the end of the time period; P_b is the population at the beginning of the time period; and B, D, IM, and OM are the number of births, deaths, in-migrants, and out-migrants during the time period, respectively.

The difference between the number of births and the number of deaths is called *natural increase* ($B - D$); it represents population growth coming from within the population itself. It may be either positive or negative, depending on whether births exceed deaths or deaths exceed births. The difference between the number of in-migrants and the number of out-migrants is called *net migration* ($IM - OM$); it represents population growth coming from the movement of people into and out of the area. It may be either positive or negative, depending on whether in-migrants exceed out-migrants or out-migrants exceed in-migrants.

For the demographic balancing equation to be exactly correct, it must apply to a geographic area with boundaries that do not change over time; in addition, there must be no measurement errors in any of the equation's variables. Since there will virtually always be errors in one or more of the variables, an error term is sometimes added to the right-hand side of the equation. This error term is often called the *residual error* or *error of closure* (Siegel 2002, p. 403). Because the error term is difficult to measure precisely, it is often lumped with one of the other terms in the equation (usually, net migration).

The demographic balancing equation is one of the most basic formulas in demography and has a number of uses. For example, if we have an accurate population count in a census year (P_b) and reliable data on births, deaths, and in- and out-migration, we can estimate the population in a later year (P_l) as:

$$\mathrm{P_l = P_b + B - D + IM - OM}$$

Another common use of the demographic balancing equation occurs when there are accurate data from two consecutive censuses and reliable data on births and deaths, but no migration data. In this case, net migration can be calculated as a residual by subtracting natural increase ($B - D$) from total population change ($P_l - P_b$):

$$\mathrm{(IM - OM) = \left(P_l - P_b\right) - (B - D)}$$

Table 2.2 shows natural increase and net migration for states for two time periods: 1990–2000 and 2000–2010. There is a tremendous amount of variability among states, especially for net migration. All states had positive natural increase (i.e., more births than deaths) between 1990 and 2000 and all but West Virginia between 2000 and 2010, but not all had positive net migration. Thirty-seven states had positive net migration in both time periods, three had negative net migration in both time periods, and 10 changed signs between the two decades. Two of the most dramatic changes occurred in Illinois and Michigan, as both states had net in-migration between 1990 and 2000 but substantial net out-migration between 2000 and 2010. It should be noted that because net migration is calculated as a residual, it includes the effects of errors in census counts and vital statistics data.

Table 2.2 Components of population change for states, 1990–2000 and 2000–2010

	1990–2000			2000–2010		
	Population change	Natural increase[a]	Net migration[b]	Population change	Natural increase[c]	Net migration
Northeast						
Connecticut	118,534	165,232	−46,698	168,447	125,109	43,338
Maine	46,851	31,293	15,558	53,582	12,470	41,112
Massachusetts	332,939	291,224	41,715	198,265	235,834	−37,569
New Hampshire	126,555	62,165	64,390	80,663	44,954	35,709
New Jersey	667,014	441,571	225,443	377,130	400,946	−23,816
New York	986,248	1,095,767	−109,519	401,076	971,273	−570,197
Pennsylvania	397,706	288,561	109,145	421,831	178,552	243,279
Rhode Island	44,795	38,031	6,764	4,308	27,638	−23,330
Vermont	45,855	23,562	22,293	17,128	13,384	3,744
Midwest						
Illinois	989,325	821,427	167,898	410,705	776,636	−365,931
Indiana	536,671	320,246	216,425	402,975	320,444	82,531
Iowa	149,707	98,780	50,927	119,817	115,127	4,690
Kansas	211,337	143,233	68,104	164,193	156,939	7,254
Michigan	643,536	560,369	83,167	−55,183	419,950	−475,133
Minnesota	543,966	285,869	258,097	384,294	329,921	54,373
Missouri	479,663	219,759	259,904	392,363	236,146	156,217
Nebraska	132,813	83,864	48,949	115,111	110,939	4,172
North Dakota	3,437	26,113	−22,676	30,354	25,412	4,942
Ohio	506,221	532,179	−25,958	183,168	415,988	−232,820
South Dakota	58,854	37,763	21,091	59,322	44,545	14,777
Wisconsin	471,988	240,995	230,993	323,229	243,030	80,199
South						
Alabama	406,818	195,392	211,426	332,529	148,485	184,044
Arkansas	322,669	92,948	229,721	242,625	111,292	131,333
Delaware	117,391	42,538	74,853	114,375	43,020	71,355
District of Columbia	−34,814	28,645	−63,459	29,637	25,118	4,519
Florida	3,044,500	437,858	2,606,642	2,818,739	518,080	2,300,659
Georgia	1,708,504	574,205	1,134,299	1,501,000	738,188	762,812
Kentucky	355,301	166,078	189,223	297,174	158,257	138,917
Louisiana	247,209	286,725	−39,516	64,337	228,198	−163,861
Maryland	515,894	333,979	181,915	476,905	315,953	160,952
Mississippi	269,279	154,413	114,866	122,543	150,189	−27,646
North Carolina	1,413,898	413,818	1,000,080	1,489,137	494,588	994,549
Oklahoma	304,875	150,341	154,534	300,900	169,789	131,111
South Carolina	525,713	210,991	314,722	613,341	194,031	419,310
Tennessee	812,224	242,081	570,143	656,678	246,497	410,181
Texas	3,864,693	1,922,477	1,942,216	4,294,533	2,297,568	1,996,965
Virginia	889,860	425,816	464,044	921,967	458,785	463,182
West Virginia	14,716	14,598	118	44,801	−968	45,769

(continued)

Table 2.2 (continued)

	1990–2000			2000–2010		
	Population change	Natural increase[a]	Net migration[b]	Population change	Natural increase[c]	Net migration
West						
Alaska	76,890	82,219	−5,329	83,298	74,205	9,093
Arizona	1,464,908	383,010	1,081,898	1,261,770	502,339	759,431
California	4,085,796	3,412,250	673,546	3,382,303	3,101,959	280,344
Colorado	1,007,613	313,030	694,583	727,110	397,694	329,416
Hawaii	103,268	113,360	−10,092	148,804	91,892	56,912
Idaho	287,223	96,049	191,174	273,625	126,335	147,290
Montana	103,135	36,067	67,068	87,215	33,954	53,261
Nevada	796,575	127,798	668,777	702,301	182,375	519,926
New Mexico	303,948	153,867	150,081	240,162	139,753	100,409
Oregon	579,187	156,019	423,168	409,550	161,540	248,010
Utah	510,333	296,308	214,025	530,702	385,583	145,119
Washington	1,027,612	383,639	643,973	830,259	376,031	454,228
Wyoming	40,197	29,185	11,012	69,840	29,946	39,894

Sources: State Population Estimates and Demographic Components of Population Change: April 1, 1990 to July 1, 1999, U.S. Census Bureau. http://www.census.gov/popest/data/state/totals/1990s/tables/ST-99-02.txt. Internet Release Date: December 29, 1999

Cumulative Estimates of the Components of Resident Population Change for the United States, Regions, States, and Puerto Rico: April 1, 2000 to July 1, 2009 (NST-EST2009-04). U.S. Census Bureau, Population Division, Internet Release Date: December 2009

[a]Natural Increase from July 1, 1999 to March 31, 2000 was estimated by taking 3/4 of the births and deaths from 7/1/1998 and 7/1/1999 and controlling them to births and deaths for the U.S. for that period

[b]Net migration is the population change less natural increase. The net migration shown here includes international and domestic migration, census enumeration errors, and errors in the births and deaths

[c]Natural Increase from July 1, 2009 to March 31, 2010 was estimated by taking 3/4 of the births and deaths from 7/1/2008 and 7/1/2009 and controlling them to births and deaths for the U.S. for that period

2.3 Statistical Measures

Demographic analysis requires the use of statistical measures. Two types can be identified. *Absolute* measures focus on single numbers such as population size, births, deaths, natural increase, or net migration. *Relative* measures focus on the relationship between two numbers; they are typically expressed as ratios, proportions, percentages, rates, or probabilities. All the relative measures are similar to each other, but each has a distinct meaning.

A *ratio* is simply one number divided by another. These could be any two numbers; they do not need to have any particular relationship to each other. For example, one could calculate the ratio of dogs to cats at the animal pound, the ratio of cars to bicycles at an intersection, or the ratio of desserts to casseroles at a potluck. To be useful, of course, the comparison of the two numbers should provide some type of meaningful information.

A commonly used ratio in demography is the sex ratio, which is the number of males divided by the number of females (typically multiplied by 100). In the United States in 2010, there were 151,781,326 males and 156,964,212 females, yielding a sex ratio of:

$$(151{,}781{,}326/156{,}964{,}212)\ (100) = (0.967)\ (100) = 96.7$$

That is, there were 96.7 males for every 100 females in the United States. Sex ratios can also be calculated for different subgroups of the population. For the U.S. population aged 85 and older in 2010, for example, the sex ratio was:

$$(1{,}789{,}679/3{,}703{,}754)\ (100) = (0.483)\ (100) = 48.3$$

That is, there were 48.3 males aged 85+ for every 100 females aged 85+. This low ratio reflects the cumulative impact of differential mortality, as males have higher mortality rates than females at every age.

A *proportion* is a special type of ratio in which the numerator is a subset of the denominator. For example, we might calculate females, Hispanics, blondes, or lefthanders as a proportion of the total population. In the United States in 2010, there were 40,267,984 people aged 65 and older and a total population of 308,745,538. The proportion 65+ can thus be calculated as:

$$40{,}267{,}984/308{,}745{,}538 = 0.130$$

If we multiply a proportion by 100, we get a *percentage*. For example, people 65 and older accounted for 13.0% of the U.S. population in 2010.

A *rate* is also a special type of ratio. A rate is the number of events occurring during a given time period divided by the population at risk of the occurrence of those events. For example, the death rate is the number of deaths divided by the population exposed to the risk of dying and the birth rate is the number of births divided by the population exposed to the risk of giving birth. In demography, rates are generally based on a period of 1 year.

Although the concept of a rate is clear, it is often difficult or impossible to develop an exact measure of the population at risk to the occurrence of an event. For example, only females in their childbearing years are exposed to the risk of giving birth. In addition, some die during the year and—for any given area—some move away while others move in. How can the population exposed to the risk of giving birth be measured?

Strictly speaking, the population at risk to the occurrence of an event is the number of person-years of exposure experienced by the population during the period under consideration (Newell 1988, p. 7). The mid-year population is often used as an approximation of the number of person-years of exposure, based on the assumption that births, deaths, and migration occur evenly throughout the year. For example, the *crude birth rate* (CBR) is calculated by dividing the number of births during the year by the mid-year population. It is often multiplied by 1,000 to express the CBR as the number of births per 1,000 persons:

$$\mathrm{CBR} = (\mathrm{B}/\mathrm{P})\ (1{,}000)$$

where *B* is the number of births during the year and *P* is the mid-year population. This is called a "crude" birth rate because the denominator—which includes men, children, and older people—is only a crude approximation of the population exposed to the risk of giving birth.

The *crude death rate* (CDR) is defined similarly:

$$\mathrm{CDR} = (\mathrm{D}/\mathrm{P})\ (1{,}000)$$

where *D* is the number of deaths during the year and *P* is the mid-year population. This is also a "crude" rate because not everyone represented in the denominator has an equal exposure to the risk of dying. For example, males have a greater likelihood of dying than females and older people have a greater likelihood of dying than younger people.

In both the CBR and the CDR, the denominator is only a rough approximation of the population exposed to the risk to the occurrence of an event. A commonly used strategy for refining crude rates is to develop rates for specific age-sex groups (racial and ethnic groups can be used as well). For age groups, the general formula is:

$${}_{\mathrm{n}}\mathrm{R}_{\mathrm{x}} = {}_{\mathrm{n}}\mathrm{E}_{\mathrm{x}}/{}_{\mathrm{n}}\mathrm{P}_{\mathrm{x}}$$

where x is the youngest age in the age interval, n is the number of years in the age interval, ${}_nR_x$ is the age-specific rate (ASR), ${}_nE_x$ is the number of events, and ${}_nP_{\mathrm{x}}$ is the mid-year population. For example, if $x = 20$ and $n = 5$, the ASR would be based on data for the population 20–24. We will give a number of examples of age-specific rates in Chaps. 4, 5 and 6, along with a variety of other demographic rates.

In addition to the distinction between crude and age-specific rates, a distinction can also be made between *central rates* and *probabilities*. In a central rate, the denominator is an area's population at the *midpoint* of a time period (typically, the middle of a year) and the numerator is the number of events occurring in the area during the time period. The denominator is meant to represent the average population during the time period, or the total number of person-years of exposure to the risk of an event. The CBR, CDR, and ASR defined above are all central rates. In a probability, the denominator is the population at the *beginning* of the time period and the numerator is the number of events occurring to that population during the time period (Rowland 2011, p. 32).

Migration makes it difficult to calculate probabilities for states and local areas. Consider age-specific death rates, for example. A true single-year probability can be calculated using the population of an area at the beginning of the year and the number of deaths occurring during the year to members of the beginning population. However, some deaths will be missed by the death registration system because they occur to people who moved out of the area before they died and some deaths will be improperly included because they occur to people who moved into the area during the year. Consequently, it is difficult (if not impossible) to construct true death probabilities. Central rates are widely used to approximate probabilities for a variety of demographic measures. As discussed in Chap. 4, central rates can be converted into probabilities when constructing life tables.

The term *rate* is used very loosely in demography, as it is elsewhere (Newell 1988, p. 7). Many measures called *rates* are really *ratios*. A growth rate, for example, is a ratio of population change over a time period to the population at the beginning of the time period. It is not a rate in a probabilistic sense because an area's growth comes not only from the population of the area itself, but from other populations as well. Another commonly used measure in demography is the *infant mortality rate*, which is the ratio of deaths to children less than age one to the number of births during the year. We will follow demographic convention in this book, using *rate* to refer to changes or events in relation to some reference population. However, we remind the reader that rates typically are not true probabilities.

2.4 Sources of Data

Demographic data are collected, produced, and distributed by a variety of federal, state, and local government agencies and private companies. Data from primary sources are available as printed publications, unpublished reports, and electronic data files. In recent years, printed publications have become less frequent as more and more data have become directly available on the Internet (see Box 2.1 for some commonly used web sites). Primary data are often replicated in secondary sources such as professional journals, textbooks, and statistical abstracts. In this section, we briefly discuss the most important sources of demographic data in the United States.

2.4.1 Decennial Census

The decennial census is the most fundamental source of demographic data in the United States. Census counts determine each state's representation in Congress and are used by state legislatures and local governments to redraw electoral boundaries. They form the basis for the distribution of hundreds of billions of dollars in federal and state funds each year through a variety of revenue-sharing and other programs. Businesses and government agencies use them for planning, budgeting, marketing, and policy-making purposes. Scholars and the media use them to analyze demographic trends. Furthermore, they form the basis for population estimates and projections made during the 10 years leading up to the following census.

Box 2.1 Some Useful Web Sites for Population and Related Data

Organization	*Web Site Address*
Federal-State Cooperative Program for Population Estimates	http://www.census.gov/popest/fscpe/
Federal-State Cooperative Program for Population Projections	http://www.census.gov/population/projections/links/fscpp/
Guttmacher Institute	http://www.guttmacher.org/index.html
Pew Research Center	http://pewresearch.org
Population Reference Bureau	http://www.prb.org
Social Security Administration	http://www.ssa.gov
State Data Centers Program	http://www.census.gov/sdc
U.S. Bureau of Economic Analysis	http://www.bea.gov/index.htm
U.S. Bureau of Labor Statistics	http://www.bls.gov
U.S. Bureau of Transportation	http://bts.gov
U.S. Census Bureau	http://www.census.gov
U.S. Geological Survey	http://www.usgs.gov
U.S. Office of Immigration Statistics	http://www.dhs.gov/immigration-statistics
U.S. National Center for Health Statistics	http://www.cdc.gov/nchs
World Bank	http://www.worldbank.org
World Factbook	http://www.cia.gov/library/publication

The first census in the United States was conducted in 1790. Data were collected by U.S. marshals and their assistants, who traveled on horseback throughout the 13 original states and four districts or territories (U.S. Census Bureau 2002). They collected information on the number of free white males older and younger than age 16, free white females of any age, all other free persons, and slaves. Most American Indians were not counted at all. Although slaves were counted, they were given a weight of only 3/5 for apportionment purposes (the famous 3/5 compromise). The marshals were not trained as census enumerators and did not follow any consistent procedures or even use a uniform questionnaire. It took them 18 months to visit all the households and tally the results (Anderson 1988, p. 14).

Many changes in census content and procedures have been made over the years. More detailed information on age, sex, and race were collected and questions were added regarding marital status, number of children, state of birth, income, education, occupation, and other characteristics. The 1940 census was the first to include a census of housing and the 1950 census was the last in which all data were collected by enumerators going door-to-door. In 1960, the Census Bureau sent questionnaires to about 60% of households by mail, asking respondents to fill out the forms and hold them until a census enumerator picked them up. This worked so well that the Census Bureau started using a mail out/mail back system for most households in 1970.

The 1940 census introduced the practice of collecting a limited amount of information from all households (sometimes called *short-form* data) and a larger amount from a sample of households (sometimes called *long-form* data). The long form asked the same questions as the short form, plus a number of other questions covering a variety of socioeconomic, demographic, and housing characteristics. The 2000 census, however, was the last to include a long form. For the 2010 census, the Census Bureau returned to the use of a single form collecting a limited amount of data. Detailed characteristics were stripped from the form and are now collected through the American Community Survey (ACS), as described below.

The starting point for the modern census is an address list developed by the Census Bureau. Called the *Master Address File* (MAF), this list is based on addresses from previous censuses and is updated using postal delivery records and data collected by local government officials. Addresses are assigned geographic coordinates such as latitude and longitude (i.e., geocoded) and allocated to specific geographic areas using the Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) system. Developed during the 1980s and first used in the 1990 census, this system includes geocodes for political and administrative boundaries and a variety of natural and man-made features as well as for the addresses contained in the MAF.

Most households are mailed census questionnaires in late March of the census year and are asked to fill them out and return them by mail; in some rural areas the forms are delivered by census enumerators. The Census Bureau follows a number of procedures designed to maximize response rates and collect information from non-responding households. In spite of these procedures, census data are incomplete and sometimes incorrect. Post-enumeration surveys and demographic analyses are used to measure the extent and nature of census errors and to develop estimates of the net undercount (or, in some instances, the net overcount).

Ever since George Washington complained about an undercount in the very first census, government officials and other interested parties have been concerned about the accuracy of census results (Anderson and Fienberg 1999, p. 29). Census errors may be caused by missed households, refusal to respond, recording errors, sampling errors, geographic assignment errors, duplication errors, coding and data-processing errors, and the incorrect imputation of missing data. The Census Bureau estimated that there were about 16 million omissions in the 2010 census (U.S. Census Bureau 2012a). These omissions were offset by a roughly equal number of duplicates. Nationally, net census undercount as measured by demographic analysis has declined considerably over time, from 5.4% in 1940 to 0.1% in 2000 (Brown et al. 2010). In 2010, there was a net *overcount* of 0.1% (Velkoff 2011)

The decennial census is a valuable source of demographic data, but it is conducted only once every 10 years and—now that the long form has been deleted—collects only a limited amount of information. Sample surveys can be used to collect data on topics not included in the decennial census and at more frequent intervals than once per decade.

2.4.2 American Community Survey

The American Community Survey (ACS) is a relatively new survey conducted by the Census Bureau. It was started on a trial basis in four sites in 1996 and expanded every year through 2005, when it became fully operational (Mather et al. 2005). The ACS samples approximately 250,000 households each month, collecting demographic, socioeconomic, and housing data similar to that previously collected in the long form of the decennial census. Data are reported annually for states, cities, counties, census tracts, block groups, and other geographic areas, but the number of months used to develop estimates depends on population size. Estimates based on 12 months of pooled data are released only for places with at least 65,000 residents. Estimates based on 36 months of pooled data are released for places with at least 20,000 residents and estimates based on 60 months are released for all places. Box 2.2 describes the types of data collected in the 2010 decennial census and the ACS.

The ACS is conducted in a manner similar to that used for the decennial census. A sample is drawn from a continuously updated MAF, with a larger proportion of addresses sampled for small governmental units than for large units. The survey follows the same mail-out/mail-back procedures as the decennial census, with non-respondents contacted through telephone calls or personal visits from Census Bureau interviewers. Responding to the ACS is required by law—as is responding to the decennial census—but there has been some discussion recently about making it voluntary.

ACS data summaries are reported in a large number of profiles, tables, and maps and are available on the Census Bureau's web site. In addition to these pre-tabulated products, data users can create custom tables and cross-tabulations using data from Public Use Microdata Sample (PUMS) files. These files contain a sample of individual records of persons and households, stripped of all identifying information. PUMS data are available for regions, divisions, states, and a variety of geographic areas with a population of at least 100,000 (U.S. Census Bureau 2009).

There are several important differences between the ACS and the decennial census. One is the definition of residence rules (Cork and Voss 2006). The decennial census follows a *de jure* approach, counting people as residents of their usual place of residence regardless of where they are on census day. The ACS has elements of both a *de jure* and *de facto* approach, as it counts people as residents of the place they are living when they receive the survey questionnaire, as long as they live there for at least 2 months. Differences in residence rules may lead to differences in results, especially in places with large numbers of snowbirds, migrant farm workers, and other types of temporary residents.

Another important difference is sample size. Whereas the sample for the 2000 census long form covered 16.7% of the addresses on the MAF, the sample for the ACS typically covers only about 2.5% per year, or 12.5% when pooled over 5 years (MacDonald 2006). This creates a substantially higher level of sampling error for ACS data than long-form data. However, the ACS may have a lower level of non-sampling error because it uses a small professional staff for non-response follow-up, whereas the decennial census uses a large workforce of temporary workers (MacDonald 2006).

Box 2.2 Data collected in the 2010 decennial census and the ACS

2010 decennial census (all households):

Population: Name, relationship to householder, sex, age, date of birth, Hispanic origin, race, and whether the person sometimes lives somewhere else.

Housing: Number of people in household and ownership status.

ACS (sample of households):

Population: Name, relationship to householder, sex, age, date of birth, Hispanic origin, race, marital status, place of birth, citizenship status, year of entry into the United States, school attendance, educational attainment, ethnic origin (ancestry), language spoken at home, fluency in English, place of residence 1 year ago, disability status, given birth within last year, living with grandchildren, military service, and a series of questions related to employment, occupation, transportation to work, and income.

Housing: Number of people in household, ownership status, type of housing unit, year built, length of residence in current unit, number of rooms, number of bedrooms, plumbing facilities, kitchen facilities, telephone service, number of motor vehicles, type of heating fuel, cost of utilities, condominium status, and whether any member of the household receives food stamps or sometimes lives somewhere else.

For single-family units or mobile homes: size of lot, sale of agricultural products, and presence of home business.

For renters: monthly rent and whether rent includes any meals.

For homeowners: value of property, real estate taxes, cost of insurance, and a series of mortgage-related questions.

Long-form data were based on a sample drawn at a single point in time; namely, the date of the decennial census. ACS data, on the other hand, are based on rolling samples covering 1-, 3-, and 5-year time periods. ACS data thus provide estimates for a period rather than for a point in time; this affects the interpretation of the results. In addition, ACS data are controlled to population estimates, whereas long-form data were controlled to decennial census counts.

The ACS clearly has several advantages compared to the census long form. By far the most important is timeliness: The ACS provides annual data over the course of a decade, whereas the decennial census provides data only once each decade. This is a tremendous advantage for many purposes. Also, non-sampling errors may be smaller because of the use of a professional staff and new questions can be added without having to wait a full decade. But there are disadvantages as well. As noted by Swanson and Tayman (2012, pp. 49–51), the smaller sample size of the ACS leads to estimates with larger sampling errors; differences in residence rules confound comparisons with population estimates and previous census results; and using pooled data washes out the effects of year-to-year changes in some variables (e.g., employment status). Furthermore, the ACS shows implausible results for some groups and geographic areas. We return to these issues in our discussion of migration rates in Chap. 6.

2.4.3 Other Surveys

The Current Population Survey (CPS) is a monthly survey of about 60,000 households conducted by the Census Bureau for the U.S. Bureau of Labor Statistics. Begun in 1940, this survey originally focused on the collection of labor force and unemployment data. It has since been expanded to cover a variety of topics including occupation, industry, education, income, veteran status, marital status, living arrangements, fertility, and migration, as well as demographic data on age, sex, race, and ethnicity. Some variables are tabulated at the national, regional, and state levels and for large metropolitan areas, but others are tabulated only at the national level. Small sample sizes can lead to erratic trends for states and metropolitan areas.

The Census Bureau also conducts the American Housing Survey and the Survey of Income and Program Participation. Both of these surveys provide useful information on demographic, socioeconomic, and housing characteristics. Again, the small sample size and nature of the sample universe limit the usefulness of these surveys for applications involving states and local areas.

2.4.4 Vital Statistics

Data on events such as births, deaths, marriages, and divorces are called *vital statistics*. In the United States, the collection of these data is the responsibility of individual states, not the federal government. As early as 1639, the Massachusetts Bay Colony began reporting births, deaths, and marriages as part of its administrative/legal system (Bryan 2004). Other states gradually began doing the same thing and today all states maintain records of births, deaths, and other vital events. The federal government sets standards for the collection and reporting of these events, compiles summaries of data collected by each state, and publishes a variety of reports based on these data. The quality of vital statistics data is generally very good in the United States and other high-income countries.

Before 1945, vital statistics reports were published by the Census Bureau. Beginning in 1945, this task was taken over by the U.S. Public Health Service, National Office of Vital Statistics. In 1960, this office was reorganized and became part of the National Center for Health Statistics (NCHS), which today is a branch of the Centers for Disease Control (CDC). Annual and monthly reports on births, deaths, marriages, and divorces are available from the NCHS. It should be noted that some of the concepts and definitions used by the NCHS do not precisely match those used by the Census Bureau (Hahn et al. 1992); as a result, adjustments may have to be made when combining population data from the Census Bureau with vital statistics data from the NCHS (Sink 1997).

Most states tabulate data at the county (or county-equivalent) level, but few go beyond that to maintain regular data series for subcounty areas (Bogue 1998). Although individual records generally contain the information needed to allocate them to different types of subcounty areas (e.g., cities, census tracts), actually doing so requires a substantial effort. Furthermore, errors in geocoding birth and death records at the subcounty level are common (Flotow and Burson 1996). Analysts needing vital statistics data for subcounty areas most likely will have to compile those data themselves.

2.4.5 Administrative Records

Administrative records are records kept by agencies of federal, state, and local governments for purposes of registration, licensing, and program administration. Although not designed specifically to do so, these records provide valuable information on demographic events and subgroups of the population. We have already discussed vital statistics, one type of administrative record commonly used in demographic analyses. Others include Social Security, Medicare, Internal Revenue Service, Office of Immigration Statistics, food stamps, drivers' licenses, building permits, school enrollment, voter registration, and property tax records. All these data sources can be used for the production of population estimates and projections. We will discuss several of these administrative records—and how they can be used for population projections—later in this book.

2.4.6 Population Estimates

A final source of demographic data is population estimates produced by federal, state, and local government agencies and private businesses. Population estimates are not primary data in the same sense as the data sources discussed above; rather, they are derived from (or based on) those data sources. They play an important role in supplementing and updating data from the other data sources.

The Census Bureau was organized as a permanent government agency in 1902. It described its plans for making population estimates in its first annual report, issued in 1903 (Bryan 2004). The plans called for estimates to be issued as of the first of June for each year after 1900, covering the nation as a whole, each state, cities of 10,000 or more, and the urban and rural parts of each state. These plans have changed considerably over time and the Census Bureau currently produces annual estimates at the national, state, and county levels by age, sex, race, and Hispanic origin. It also makes annual estimates for cities, towns, and townships, but only for the total population.

Many state and local government agencies make population estimates. Some states produce independent population estimates at the state, county, and/or city level, while others rely on estimates produced by the Census Bureau. Most states (along with the Census Bureau) participate in the Federal-State Cooperative

Program for Population Estimates (FSCPE), which serves as a conduit for exchanging demographic data and as a forum for discussing and evaluating population estimation techniques and data sources. Some city and county governments—and Councils of Governments or Metropolitan Planning Organizations for large metropolitan areas—also produce population estimates, often for small areas such as census tracts and traffic analysis zones. Finally, several private companies produce estimates at the county and subcounty levels. Further information on the production of population estimates can be found in Murdock and Ellis (1991), Rives et al. (1995), Siegel (2002), and Swanson and Tayman (2012).

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Chapter 3
Overview of the Cohort-Component Method

We begin our discussion of population projection methods with the cohort-component method, which has a longstanding tradition in demography (Bowley 1924; Cannan 1895; Whelpton 1928). The Census Bureau began using this method for national projections in the 1940s and for state projections in the 1950s and has used some version of the method ever since. A survey conducted by the Federal-State Cooperative Program for Population Projections found that 89% of states making state-level projections of total population used some form of the cohort-component method; for states making projections by age, sex, and race, 95% used the cohort-component method (Judson 1997). It is also widely used for projections at the county and subcounty level. Although current applications of the cohort-component method are more detailed and sophisticated than the earliest applications, its basic framework is much like it was 100 years ago.

The cohort-component method is so widely used because it provides a flexible yet powerful approach to population projection. It can incorporate many application techniques, types of data, and assumptions regarding future population change. It can be used at any level of geography, from nations down to states, counties, and subcounty areas. Perhaps most important, it provides projections not only of total population but also of demographic composition and individual components of growth. The cohort-component method provides a good starting point for the study of state and local population projections.

3.1 Concepts and Terminology

A *cohort* may be defined as a group of people who experience the same demographic event during a particular period of time and who may be identified at later dates on the basis of this common experience (Shryock and Siegel 1973, p. 712). For example, all babies born during the 1990s comprise the birth cohort for that decade; all persons married in 2005 form the marriage cohort for that year; and all immigrants entering the United States between 2010 and 2012 make up the immigration cohort for that

S.K. Smith et al., *A Practitioner's Guide to State and Local Population Projections*, The Springer Series on Demographic Methods and Population Analysis 37,
DOI 10.1007/978-94-007-7551-0_3,

3-year period. Cohorts can be defined for other significant events as well, such as graduation from college or entry into the labor force.

For purposes of population projection, breaking the total population into separate age cohorts was an important methodological innovation. Such a breakdown allows the analyst to account for the substantial differences in mortality, fertility, and migration rates found among different cohorts and to consider how those rates change over time. For example, fertility rates are typically higher for women in their late 20s than for women in their late 30s, but the rates for both groups rose during the 1940s and 1950s and declined during the 1960s and 1970s. Mortality rates for infants are higher than mortality rates for teenagers, but declined more rapidly during the twentieth century. Migration rates are typically highest for people in their 20s, but age patterns vary from place to place and change over time.

Age cohorts are typically split between males and females and are often subdivided by race and ethnicity; occasionally, they are subdivided by other characteristics as well. These divisions allow the analyst to account for additional types of demographic variation and permit the construction of more finely detailed projections.

The components of population change (births, deaths, and migration) were described in Chap. 2. For several reasons, it is useful to distinguish among these components when producing population projections. First, such distinctions enable us to account separately for the demographic causes of population change. Is an area changing primarily because of natural increase or net migration? Is the birth rate unusually high or the death rate unusually low? Are in-migrants coming mostly from other parts of the same state, from other states, or from abroad? If a population is aging rapidly, is it because older people are moving in or younger people are moving out? Making these distinctions is the first step in gaining insight into why some areas are growing more rapidly than others and why growth rates and demographic composition change over time.

Second, each component of change responds differently to changes in economic, social, political, cultural, medical, environmental, and other factors. For example, medical advances lead to greater life expectancies but have little impact on migration, whereas changing employment conditions have a substantial impact on migration but little impact on life expectancies. Developing an understanding of non-demographic causes of population change requires that population change be broken down into its individual components.

Finally, the behavior of each component of change varies among places and follows different trends over time. In one area, for example, the number of births may be increasing and the number of deaths declining, while in another area the opposite is occurring. In-migrants may exceed out-migrants in one county while out-migrants exceed in-migrants in another. Separating the components of change enables the analyst to account for these differences when developing assumptions about future population trends.

Information on the components of population change is important for many types of population analysis. Information on the demographic composition of the population (i.e., its breakdown by age, sex, race, and other characteristics) is also

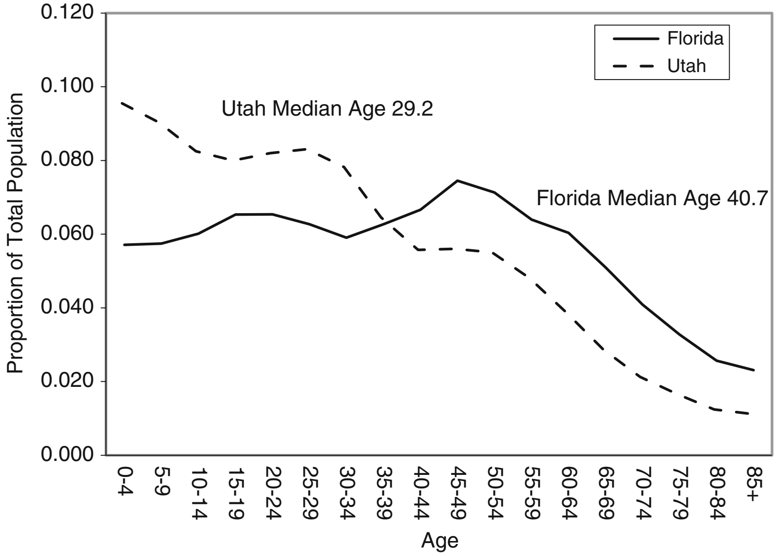

Fig. 3.1 Age distribution, States of Florida and Utah, 2010 (Source: U.S. Census Bureau, 2010 census)

important because overall birth, death, and migration patterns are strongly affected by these characteristics. For example, births occur primarily to women between the ages of 15 and 44, death rates are much higher for older persons than younger persons, and migration rates are typically highest for people in their 20s and decline steadily thereafter. Differences in demographic composition can have a major impact on a population's birth, death, and migration patterns.

Demographic composition differs considerably among states, counties, and subcounty areas. Figure 3.1 shows the 2010 age structures for Utah and Florida. Geographically, these states are on opposite sides of the continent; demographically, their age characteristics are at opposite ends of the spectrum as well, with Utah having one of the youngest populations of any state and Florida one of the oldest (Howden and Meyer 2011). These differences in age structure contribute to Utah's relatively high rate of natural increase and Florida's relatively low rate. Partly as a result of these differences, natural increase accounted for 73% of the population growth in Utah between 2000 and 2010, whereas in Florida it accounted for only 18% (see Table 2.2).

Differences in demographic composition are even greater among counties and subcounty areas than among states. In Florida, for example, 43% of the population in Sumter County was 65 and older in 2010, compared to only 9% in Leon County. Just over 56% of the population in Gadsden County was black, compared to less than 3% in Citrus County. More than 65% of the population in Miami-Dade County was of Hispanic origin, compared to less than 2% in Baker County (Bureau of Economic and Business Research 2012). Local variations like these are found throughout the nation. The cohort-component method allows the analyst to account for these variations when developing population projections.

3.2 Brief Description of Procedures

By today's standards, the earliest applications of the cohort-component method were somewhat crude (Bowley 1924; Cannan 1895). Although they projected the components of population change separately, early models did not fully account for the effects of differences in age, sex, and racial composition on births, deaths, and migration. This soon changed and birth and death rates were calculated separately for each age-sex cohort in the population (Whelpton 1928). Cohort-component models have since been extended to cover differences by race and ethnicity as well (Campbell 1996; Ortman and Guarneri 2009). Figure 3.2 provides an overview of the steps involved in applying the cohort-component method.

The starting point is the launch-year population (i.e., the population at the beginning of the projection period) divided into age-sex cohorts. Age cohorts can be defined in a number of ways, but 1- and 5-year groups are the most common. As we show in Chap. 7, the construction of projections is simpler if the number of years in the projection interval is equal to or exactly divisible by the number of years in the age cohort (e.g., 5-year age cohorts for projections made in 5- or 10-year

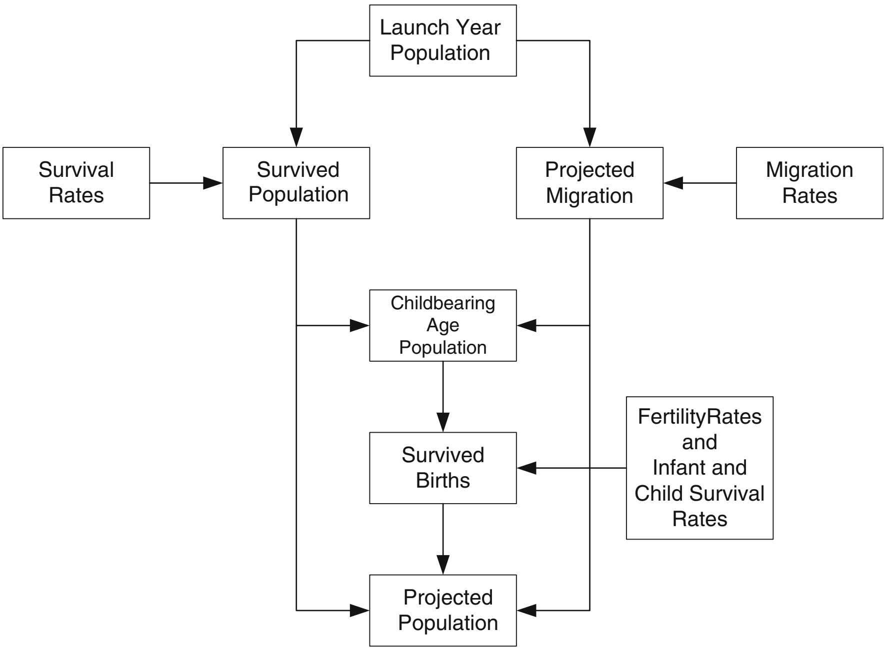

Fig. 3.2 Overview of the cohort-component method

intervals, but not for projections made in 1-year intervals). The oldest cohort is typically 75+ or 85+, although 100+ is sometimes used. Many applications of the cohort-component method further subdivide the population by race and ethnicity. This adds to the data requirements and number of calculations, but the logic and procedures remain the same.

The first step in the projection process is to calculate the number of persons surviving to the end of the projection interval. This is accomplished by applying age-sex-specific survival rates to each age-sex cohort in the initial population. These survival rates reflect the probability of surviving throughout the projection interval; they are commonly based on life tables derived from compilations of recent mortality data. Future survival rates can be based on the extrapolation of historical trends, structural models, simulation techniques, or rates found in other areas. Chapter 4 describes a number of approaches used for projecting survival rates, the mortality component of population growth.

The second step is to project migration during the projection interval. Migration rates are calculated for each age-sex cohort in the population. These rates can be based on either gross migration data (i.e., separate calculations for in-migrants and out-migrants) or net migration data (i.e., one calculation reflecting the net change due to migration). Projections of future rates can be based on recent values, trend extrapolations, simulated values, model schedules, or structural models. The application of projected migration rates provides a projection of the number of persons in each age-sex cohort who move into or out of an area during the projection interval (or, for models using net migration data, the net change due to migration). These numbers are added to or subtracted from the surviving population to provide a projection of persons born before the launch date (e.g., persons aged five and older for a 5-year projection interval). Chapter 6 discusses sources of migration data and several approaches to projecting migration rates.

The third step is to project the number of births occurring during the projection interval. This is accomplished by applying age-specific birth rates to the female population in each age cohort. Projected birth rates can be based on recent values, trend extrapolations, simulated values, model schedules, or structural models. Chapter 5 describes sources of fertility data and several approaches to projecting birth rates.

The final step in the process is to add the number of births (distinguishing between males and females and adjusting for migration and mortality) to the rest of the population, providing a projection of the total population by age and sex at the end of the projection interval. This population serves as the base for projections over the following interval. The process is repeated until the final target year in the projection horizon has been reached. Chapter 7 gives several step-by-step examples of the entire process and discusses the strengths and weaknesses of the cohort-component method.

The logic underlying the cohort-component method is simple and straightforward. Collecting the data and developing the assumptions and procedures needed to apply the method, however, is much more complicated. The next three chapters provide a detailed description of the data sources, statistical measures, theoretical perspectives, and projection techniques that can be used for projecting the three components of population change. We start with mortality, the simplest of the three to forecast accurately. We then consider fertility, which presents more challenges. We conclude with migration, the most difficult component to forecast accurately at the state and local level.

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Chapter 4
Mortality

Survival has been a central preoccupation of humankind since the origin of the species. For most of history, however, human beings have not been particularly successful at fending off deprivation, disease, destruction, and death. As recently as 200 years ago, life expectancy at birth was only 30–40 years, even in the most economically advanced countries. These levels were not much higher than they had been thousands of years earlier. In many low-income countries, life expectancies remained at very low levels well into the twentieth century.

Substantial increases in life expectancies have occurred over the last century or two. Driven by improved standards of living and scientific, medical, and public health advances, life expectancies at birth have risen to the upper 70s or low 80s in most high-income countries and the upper 60s or low 70s in many low- and middle-income countries. Even the world's poorest countries typically have life expectancies of at least 50. These changes have had a dramatic impact on the size and composition of the human population.

Life expectancy at birth in the United States rose from 47 to 77 during the twentieth century and increased by more than a year between 2000 and 2010. It has been estimated that more than 68 million Americans alive in 2000 (about 25% of the total population) would have died without the improvements in survival rates occurring after 1900; another 25% would never have been born because their ancestors would have died before having children (White and Preston 1996). Given the magnitude of past changes, the potential for future changes, and the differences found among demographic groups, mortality clearly plays a central role in the production of cohort-component population projections.

We start this chapter with a description of several mortality measures. We then discuss survival, the converse of mortality: A person either lives from one point in time to another or dies during that interval. We consider two types of survival rates, focusing primarily on the one used most frequently for projections in the United States. We discuss the data sources and techniques used in constructing survival rates and consider several perspectives regarding future mortality trends. We pay particular attention to the special problems of projecting survival rates for states and

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DOI 10.1007/978-94-007-7551-0_4,

local areas and close with an assessment of the impact of mortality assumptions on population projections.

4.1 Mortality Measures

The most commonly used mortality measures relate the number of deaths during a particular period (usually a year) to the number of person-years of exposure to the risk of dying (usually approximated by the midyear population). These measures are typically defined as mortality rates, but are not rates in a true probabilistic sense (see Chap. 2 for an explanation). In the United States, the mortality data used as numerators for constructing mortality rates are collected by the vital statistics agencies of each state and compiled by the National Center for Health Statistics (NCHS). The population data used as denominators are taken from either decennial censuses or intercensal estimates, depending on the year(s) for which the rates are to be constructed.

4.1.1 Crude Death Rate

The simplest measure of mortality is the crude death rate (CDR), which is calculated by dividing the number of deaths during a year by the midyear population. It is generally multiplied by 1,000 to reflect the number of deaths per 1,000 persons:

$$\mathrm{CDR} = (\mathrm{D}/\mathrm{P})\ (1{,}000)$$

where D is the number of deaths during the year and P is the midyear population. For example, there were 2,465,936 deaths in the United States in 2010 and the midyear population was estimated as 309,349,689, yielding a CDR of:

$$(2{,}465{,}936/309{,}349{,}689)\ (1{,}000) = 8.0$$

This means there were 8 deaths for every 1,000 residents of the United States in 2010. Crude death rates can be calculated separately for males and females and for various racial, ethnic, occupational, educational, and other subgroups of the population. For example, the CDR in the United States in 2010 was 7.9 for females and 8.1 for males:

$$\text{Females}: (1{,}234{,}721/157{,}241{,}696)\ (1{,}000) = 7.9$$
$$\text{Males}: (1{,}231{,}215/152{,}107{,}993)\ (1{,}000) = 8.1$$

Crude death rates can be calculated for different geographic regions as well. In 2010, CDRs for states ranged from 5.2 in Alaska to 11.5 in West Virginia (Murphy et al. 2012). For nations, CDRs ranged from 1 per 1,000 in Qatar and the United Arab Emirates to 16 or 17 in Afghanistan, Chad, Nigeria, and the Demographic Republic of Congo (Population Reference Bureau 2011).

The CDR provides an indication of the incidence of deaths relative to the overall size of a population. For many purposes, however, the usefulness of the CDR is limited because it does not account for one of the major determinants of mortality; namely, the age structure of the population. A young age structure is a major reason why the 2010 CDR for blacks (6.8) was lower than the CDR for whites (8.6) in the United States, and why the CDR for Alaska (5.2) was lower than the CDR for West Virginia (11.5). A second mortality measure deals with this problem by focusing on deaths within each age group.

4.1.2 Age-Specific Death Rate

An age-specific death rate (ASDR) shows the proportion of persons in each age group (x to $x + n$) that dies during a year:

$$ {}_{\mathrm{n}}\mathrm{ASDR}_{\mathrm{x}} = {}_{\mathrm{n}}\mathrm{D}_{\mathrm{x}} / {}_{\mathrm{n}}\mathrm{P}_{\mathrm{x}} $$

where x is the youngest age in the age interval, n is the number of years in the age interval, ${}_nD_x$ is the number of deaths of persons between the ages of x and $x + n$ during the year, and ${}_nP_x$ is the mid-year population of persons between the ages of x and $x + n$. For example, there were 111,908 deaths to males aged 45–54 in the United States in 2010, and a midyear population of 22,148,815 males aged 45–54, yielding an ASDR of:

$$ {}_{10}\mathrm{ASDR}_{45} = 111{,}908/22{,}148{,}815 = 0.0051 $$

ASDRs are typically calculated for 1-, 5-, or 10-year age groups. They are called *central death rates* (denoted as ${}_nm_x$) because they are based on the average population during the year, typically represented by the midyear population. To control for short-run fluctuations, ASDRs are often based on a 3-year average rather than a single year of mortality data; such adjustments are particularly important for places with small populations. ASDRs are generally calculated separately for males and females because of their well-known differences in longevity. They can also be calculated separately for different races, ethnic groups, and other demographic categories.

ASDRs are often expressed in terms of deaths per 100,000 persons. This conversion is made by multiplying the ASDR by 100,000. In the example shown above, the ASDR of 0.0051 can be expressed as 510 deaths per 100,000 males aged 45–54. Figure 4.1 shows ASDRs for males in the United States in 2010. The J-shaped pattern reflects the relatively high death rates for newborn babies, the considerably lower rates for young children, the slowly increasing rates at the middle ages, and the more

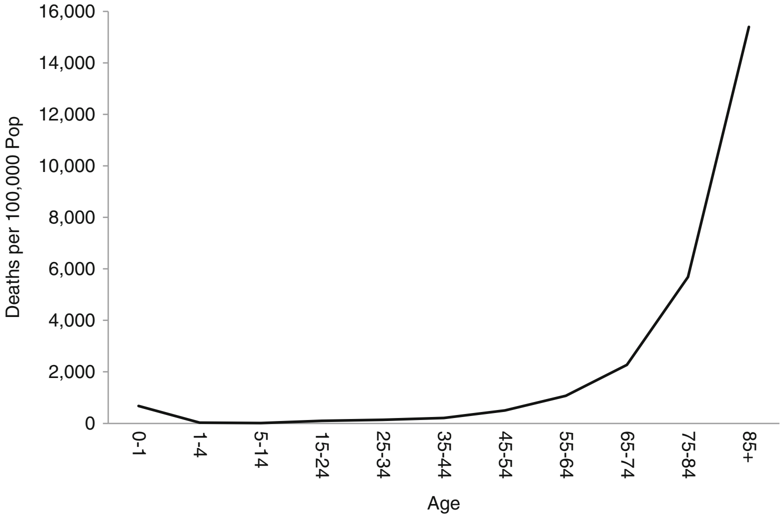

Fig. 4.1 Age-specific death rates for males, United States, 2010 (Source: National Center for Health Statistics, National Vital Statistics Reports, Vol 60, No. 4, Hyattsville, Maryland, 2012)

rapidly increasing rates at the older ages. This general pattern is found for virtually every population and population subgroup throughout the world. Although some studies have found the rate of increase in mortality rates to slow down in the oldest age groups (Horiuchi and Wilmoth 1998), others have questioned this finding (Gavrilov and Gavrilova 2011).

4.2 Survival Rates

Survival rates show the probability of surviving from one age (or age group) to another. There are two main approaches to constructing survival rates. One is based on life tables, which are statistical tables summarizing a population's mortality characteristics. The other is based on a comparison of age cohorts in two consecutive censuses. The first is used much more frequently than the second for places with good vital statistics data, but the second is useful for places lacking such data. Also, the second approach can be very useful when the focus is on population change over time rather than on survival rates per se.

4.2.1 Life Table Survival Rates

Life tables have a long history. In fact, the origins of formal demography are often traced to Englishman John Graunt, who analyzed mortality records for London in the 1660s and developed a precursor to the modern life table (Weeks 2012, p. 73). Other inexact life tables based on limited data were prepared for several places in Europe during the seventeenth and eighteenth centuries. Joshua Milne constructed the first scientifically correct life table for several parishes in England in 1815.

The first official life tables for the United States were prepared for 1900–1902 and have been produced at least once each decade ever since. Annual life tables for the nation as a whole have been prepared every year since 1945. Life tables for individual states have been produced in conjunction with every decennial census since 1930, albeit with varying levels of detail for racial/ethnic groups. Life tables for the urban and rural populations and for metropolitan and non-metropolitan areas also have been produced on occasion (Kintner 2004).

4.2.1.1 Constructing Life Tables

The principal focus of a life table is the probability of dying between one exact age and another. The starting point for constructing a life table for a particular year is a complete set of ASDRs for that year (the ${}_nm_x$ values described above). ASDRs, however, are based on midyear population estimates. They do not provide exact measures of the probability of dying because some people die before midyear. The denominators of ASDRs therefore must be adjusted to account for deaths occurring during the year. This is often done by assuming that deaths are evenly distributed throughout the year. Using this assumption, the proportion dying during a specific time interval (that is, the probability of dying between two exact ages) can be calculated as:

$$ {}_\mathrm{n}\mathrm{q}_\mathrm{x} = {}_\mathrm{n}\mathrm{D}_\mathrm{x}/[{}_\mathrm{n}\mathrm{P}_\mathrm{x} + (0.5)\ ({}_\mathrm{n}\mathrm{D}_\mathrm{x})] $$

If we divide both the numerator and denominator by ${}_nP_x$, we can express the proportion dying (${}_nq_x$) as a function of the central death rate (${}_nm_x$):

$$ {}_\mathrm{n}\mathrm{q}_\mathrm{x} = {}_\mathrm{n}\mathrm{m}_\mathrm{x}/[1 + (0.5)\ ({}_\mathrm{n}\mathrm{m}_\mathrm{x})] $$

This transformation of ${}_nm_x$ into ${}_nq_x$ is an approximation; its accuracy depends on the degree to which deaths are evenly distributed throughout the year. This assumption will be valid for most age groups, but not for the very young or (to a lesser extent) the very old. The validity of this assumption will also be reduced for areas in which the population is growing (or declining) very rapidly.

The elements of a life table are defined as follows:

1. ***Proportion dying*** (${}_nq_x$)—The proportion of persons who are alive at exact age x but die before reaching exact age $x + n$. An *exact age* refers to a birthday. For example, ${}_5q_{30}$ refers to the proportion of persons alive on their 30th birthday who die before reaching their 35th birthday.

2. ***Number surviving*** (l_x)—The number of persons who survive to exact age x, out of a beginning cohort of 100,000 live births (called the *radix*).
3. ***Number dying*** ($_nd_x$)—The number of deaths between exact ages x and $x + n$, out of the number of persons alive at the beginning of that interval.
4. ***Person-years lived during an age interval*** ($_nL_x$)—The summed total of person-years lived between exact ages x and $x + n$, based on each person's record of survival during that age interval. For example, a person living from age 60 to 65 would count as five person-years lived during this 5-year interval; a person dying at exact age 64 would count as four person-years lived.
5. ***Total person-years yet to be lived*** (T_x)—The summed total of person-years lived during this and all following age intervals.
6. ***Life expectancy*** (e_x)—The average number of years of life remaining to persons alive at exact age x.

There are two types of life tables. A *period life table* is based on the ASDRs calculated for a particular period of time (usually 1, 2, or 3 years). For example, recent life tables prepared by the NCHS were based on mortality data and population estimates for 2007 (Arias 2011). Life tables for states are typically based on mortality data covering a 3-year period (e.g., 2009–2011) and population data for the midpoint of that period (e.g., 2010). Period life tables may be interpreted as showing the lifetime mortality patterns that would be experienced by a cohort of newborn babies if the age-specific death rates observed at the time of their births continued unchanged throughout their lifetimes.

A *cohort life table*, on the other hand, is based on the mortality patterns actually experienced by members of a particular birth cohort (e.g., all persons born in 1900) over their lifetimes. Age-specific death rates are calculated at each age as the cohort moves from infancy through old age. Obviously, cohort life tables require many more years of data than period life tables; consequently, they can be constructed only for cohorts born long ago. Although they are valuable for analyzing mortality trends over time, they are not very useful for producing population projections. In this book we consider only period life tables. An example of cohort life tables for the United States can be found in Bell and Miller (2005).

Life tables also can be classified as complete or abridged. *Complete* (unabridged) life tables provide data by single year of age; *abridged* life tables provide data by age group (usually 5-year groups, with the youngest group subdivided at age one). Both types can be used for population projections. Unabridged life tables are particularly useful for making projections by single year of age and for single-year time horizons, whereas abridged life tables are particularly useful for making projections for 5- or 10-year age groups and 5- or 10-year time horizons. Table 4.1 shows an abridged period life table for the U.S. population in 2007 (Arias 2011).

Life tables are useful not only for mortality projections, but for many other purposes as well. The same techniques used to measure mortality can be used to measure the duration of variables such as marriage, employment, education, and the housing stock. When two or more variables are combined into one life table, it is

Table 4.1 Abridged life table, total population, United States, 2007

				Person years lived		
	Probability of dying during age interval	Number surviving to age *x*	Number dying during age interval	In the age interval	In this and all subsequent age intervals	Average expectation of life at age *x*
Age	${}_nq_x$	l_x	${}_nd_x$	${}_nL_x$	T_x	e^o_x
0–1	0.006761	100,000	676	99,406	7,793,398	77.9
1–4	0.001140	99,324	113	397,023	7,693,992	77.5
5–9	0.000683	99,211	68	495,870	7,296,969	73.6
10–14	0.000839	99,143	83	495,562	6,801,099	68.6
15–19	0.003089	99,060	306	494,626	6,305,537	63.7
20–24	0.004906	98,754	485	492,591	5,810,911	58.8
25–29	0.004959	98,269	487	490,128	5,318,320	54.1
30–34	0.005524	97,782	540	487,600	4,828,192	49.4
35–39	0.007251	97,242	705	484,547	4,340,592	44.6
40–44	0.011003	96,537	1,062	480,214	3,856,045	39.9
45–49	0.016870	95,475	1,611	473,601	3,375,831	35.4
50–54	0.025217	93,864	2,367	463,734	2,902,230	30.9
55–59	0.035858	91,497	3,281	449,712	2,438,496	26.7
60–64	0.052469	88,216	4,629	430,149	1,988,784	22.5
65–69	0.077792	83,587	6,502	402,523	1,558,635	18.6
70–74	0.119029	77,085	9,175	363,858	1,156,112	15.0
75–79	0.191303	67,910	12,991	308,631	792,254	11.7
80–84	0.297772	54,918	16,353	234,712	483,622	8.8
85–89	0.441837	38,565	17,040	149,648	248,911	6.5
90–94	0.612543	21,526	13,185	72,247	99,263	4.6
95–99	0.778938	8,340	6,497	22,835	27,016	3.2
100+	1.000000	1,844	1,844	4,181	4,181	2.3

Source: National Center for Health Statistics, National Vital Statistics Reports, *United States Abridged Life Tables, 2007, 59*(9), Hyattsville, Maryland, 2011

called a *multiple-decrement* table. For example, mortality and divorce can be combined into one life table for married persons, with changes in marital status being caused by either death or divorce. An extension of this technique with particular relevance to many planners and policy makers combines mortality rates with disability rates, providing an indication of changing needs for medical care, living assistance, and institutionalization (Crimmins et al. 1997). Life tables also play an important role in the highly mathematical field of *stationary population analysis*. When used in this manner, some elements of the life table take on a different interpretation than the ones given above (Kintner 2004).

The idea behind a period life table is clear: it summarizes the mortality (and survival) probabilities observed in a particular population during a particular period of time. The actual construction of a life table is not as simple as it might appear, however. Problems include adjusting for the accuracy of the underlying death and population data; smoothing out data fluctuations over time; adjusting for the digit preference often found in age data reported in censuses and surveys; matching deaths during a calendar year with changes in age during the year; transforming observed age-specific death rates into survival probabilities; and developing techniques for converting unabridged to abridged life tables (and vice versa). For more detailed discussions of life tables—including the use of Lexis diagrams that combine period and cohort effects—see Bell and Miller (2005), Kintner (2004), and Smith (1992).

4.2.1.2 Constructing Life Table Survival Rates

In countries with good vital statistics data, life tables provide the most frequently used source of data for calculating survival rates. For population projections, survival rates are often based on 5-year time horizons and 5-year age groups and are calculated as:

$$_5S_x = {_5L_{x+5}}/{_5L_x}$$

where $_5L_{x+5}$ is the number of person-years lived between ages $x + 5$ and $x + 10$, and $_5L_x$ is the number of person-years lived between ages x and $x + 5$. For the U.S. population aged 20–24 in 2007, for example, the 5-year survival rate is:

$$_5L_{25}/{_5L_{20}} = 490{,}128/492{,}591 = 0.9950$$

In other words, given these survival rates, only about 5 out of 1,000 persons aged 20–24 in 2007 would be expected to die during the following 5 years.

Survival rates can be calculated for different time horizons and different age groups by changing the subscripts in the equation shown above. For example, a 10-year survival rate for a 5-year age group can be calculated as:

$$_{10}S_x = {_5L_{x+10}}/{_5L_x}$$

Using the data in Table 4.1, a 10-year survival rate for persons aged 20–24 is:

$$_5L_{30}/{_5L_{20}} = 487{,}600/492{,}591 = 0.9899$$

Due to the peculiar nature of mortality patterns in the first year of life, the 0–4 age cohort is often split into two groups: less than 1 and 1–4. Survival rates are calculated separately for each group. Rates for children aged 1–4 are often calculated in the manner described above, but rates for infants less than age 1 are based on procedures which account for the high mortality rates occurring in the first days and weeks of life. Making this distinction may be important when the size of the newborn cohort has been changing rapidly or when the projections are used for detailed analyses of mortality.

The procedure for calculating survival rates for the oldest age group is slightly different because it is an open-ended group. For this age group, T-values rather than

L-values are used. Suppose that 85+ is the oldest age group to be projected. The 5-year survival rate for this age group is calculated as:

$$S_{80} = T_{85}/T_{80}$$

where T_{85} and T_{80} are the total person-years lived after ages 85 and 80, respectively. Using the data in Table 4.1, the 5-year survival rate for persons aged 80+ is calculated as:

$$T_{85}/T_{80} = 248{,}911/483{,}622 = 0.5147$$

In other words, given the continuation of 2007 mortality rates, only 51.5% of the population aged 80+ would be expected to live for at least five more years. This stands in sharp contrast to the 99.5% survival rate for the population aged 20–24.

Calculating survival rates for 1-year age groups requires an unabridged life table, but the approach is the same. For example, a 5-year survival rate for a 1-year age group can be calculated as:

$$S_x = L_{x+5}/L_x$$

Using data from an unabridged life table for the United States in 2007 (Arias 2011), we can calculate the 5-year survival rate for 50-year-old males as:

$$L_{55}/L_{50} = 88{,}942/91{,}993 = 0.9668$$

Survival rates are typically calculated separately for males and females and often are further subdivided by race and ethnicity. The reason for drawing these distinctions is that mortality rates vary from one demographic subgroup to another. Table 4.2 shows that ${}_nq_x$ values in the United States are highest for black males and lowest for white females in every age group. Rates for white males and black females fall somewhere in between. The use of separate rates is essential when projections are made for different demographic subgroups, of course, but may also be important when those subgroups are growing at different rates and have survival rates that differ substantially from each other.

Although the NCHS publishes complete U.S. life tables for males and females and for several racial/ethnic groups on an annual basis, it no longer publishes abridged life tables for these demographic subgroups. However, abridged tables can be constructed easily from complete tables by applying a set of simple calculations (Arias 2011). We used those calculations to develop the ${}_nq_x$ values shown in Table 4.2.

Table 4.2 Life table mortality rates ($_nq_x$) by age, sex, and race, United States, 2007

Age	White females	White males	Black females	Black males
0–1	0.00508	0.00618	0.01197	0.01451
1–4	0.00092	0.00113	0.00155	0.00180
5–9	0.00059	0.00070	0.00078	0.00102
10–14	0.00065	0.00091	0.00091	0.00141
15–19	0.00179	0.00398	0.00187	0.00639
20–24	0.00233	0.00678	0.00308	0.01058
25–29	0.00264	0.00651	0.00432	0.01130
30–34	0.00333	0.00688	0.00597	0.01276
35–39	0.00482	0.00861	0.00902	0.01555
40–44	0.00763	0.01295	0.01366	0.02190
45–49	0.01179	0.01983	0.02166	0.03349
50–54	0.01727	0.02989	0.03220	0.05427
55–59	0.02521	0.04248	0.04379	0.07811
60–64	0.03935	0.06191	0.06219	0.10764
65–69	0.06075	0.09230	0.08808	0.14507
70–74	0.09656	0.14170	0.12808	0.20022
75–79	0.16244	0.22553	0.19432	0.28126
80–84	0.26516	0.34518	0.28616	0.38090
85+	1.00000	1.00000	1.00000	1.00000

Source: National Center for Health Statistics, National Vital Statistics Reports, *United States Abridged Life Tables, 2007 59*(9), Hyattsville, Maryland, 2011

4.2.2 Census Survival Rates

The second approach to constructing survival rates does not require age-specific mortality data, making it particularly useful for countries (or regions) lacking vital statistics data. This approach is based on the formation of ratios between age cohorts in two consecutive censuses. These ratios are called *census survival rates* and are calculated as:

$$_nS_x = {_nP_{x+t,c+t}} / {_nP_{x,c}}$$

where *x* is the youngest age in the age interval, *n* is the number of years in the age interval, *P* is the population size, *c* is the year of the second most recent census, and *t* is the number of years between the two most recent censuses. In the United States, for example, 16,817,924 residents aged 60–64 were counted in the 2010 census and 17,585,824 residents aged 50–54 were counted in the 2000 census, yielding a census survival rate of:

$$_5P_{60,2010} / {_5P_{50,2000}} = 16{,}817{,}924/17{,}585{,}824 = 0.9563$$

Census survival rates are typically constructed separately for males and females and can be further differentiated by race, ethnicity, and other demographic characteristics as well.

This approach to constructing survival rates has several problems. The most important is that the size of a cohort changes not only because of deaths but also because of people moving into and out of an area. Consequently, census survival rates mix the effects of mortality and migration and give misleading estimates of survival probabilities for places with even moderate levels of in- or out-migration.

A second problem is that census survival rates are affected by changes in coverage from one decennial census to the next. As noted in Chap. 2, no census enumeration is perfect. Some people are missed, some are counted twice, and others are counted in the wrong place. If coverage rates were the same in every census and in every demographic subgroup, enumeration errors would create no major problems for constructing census survival rates. However, because coverage rates differ from one subgroup to another and change over time, changes in coverage rates introduce additional errors into the estimation of census survival rates.

Because of these problems, census survival rates are seldom used for mortality projections in countries with good vital statistics data. As shown in Chaps. 6 and 7, however, they can be used as measures of the *joint* effect of mortality and migration, making them very useful for constructing population projections for areas lacking good migration data. For the remainder of this chapter, our discussion focuses solely on life table survival rates.

4.3 Approaches to Projecting Mortality Rates

Mortality rates in the United States have been declining for many years. Figure 4.2 shows trends in female mortality rates for selected age groups between 1900 and 2010. Rates have fallen in every age group, especially the youngest. Similar declines occurred for males as well. Will mortality rates continue declining in the future? If so, how rapidly will they decline? If not, why not? Answers to these questions are central to the construction of population projections and a variety of approaches can be used for projecting mortality and survival rates.

4.3.1 Constant Rates

The simplest approach is to assume that recent mortality rates will continue unchanged. This assumption will generally be reasonable for short projection horizons of 5 or 10 years because mortality rates in more developed countries are very low for most age groups and change relatively slowly over time, especially for the younger and middle age groups. For longer horizons, however, the no-change assumption may not be reasonable.

In most instances, we believe it is advisable to develop assumptions that take into account potential changes in mortality rates. Mortality rates in the United States have been declining for many decades and—although a reversal could

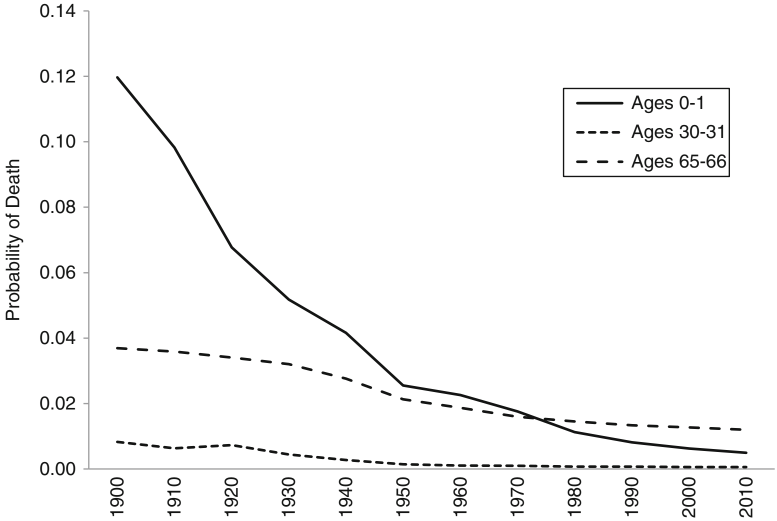

Fig. 4.2 Period probabilities of death ($_nq_x$) for selected female exact ages, United States, 1900–2010 (Source: Bell et al. (2005))

occur—most observers believe the chances that rates will continue declining are greater than the chances that they will remain constant or increase. It must be noted, however, that mortality rates have not fallen uniformly in all geographic regions or among all demographic groups, and many counties in the United States have fallen behind in international comparisons of life expectancy in recent years (Kulkarni et al. 2011).

The analyst must make a carefully reasoned assessment of recent mortality trends and develop assumptions consistent with those trends. If it is assumed that mortality rates are likely to change, there are a number of ways to project those rates into the future. Following Olshansky (1988), we identify several basic approaches to projecting mortality rates: the movement of current rates toward those observed in a target population; the extrapolation of past trends; the reduction or elimination of particular causes of death; tying future changes in mortality rates for one area to changes projected for another area; and soliciting the input of a panel of experts.

4.3.2 Targeting

The targeting approach is based on the assumption that mortality rates in the population to be projected will gradually converge toward those observed in another population (i.e., the target). A target population is chosen which provides a set of mortality rates believed to be realistic for the population to be projected. This choice is based on similarities in socioeconomic, cultural, and behavioral characteristics; levels of medical technology; primary causes of death; and similar factors. Statistical techniques ranging from simple percent reductions to complex curve-fitting procedures can be used to guide the convergence of one set of rates to another (Olshansky 1988).

The targeting approach has been around almost as long as the cohort-component method itself and is frequently used, often in conjunction with other techniques. Whelpton (1928) used targeting techniques for projections of the U.S. population, with mortality rates in New Zealand used as target rates toward which U.S. rates would move over a 50-year period. Nakosteen (1989) projected that county mortality rates in Massachusetts would gradually move toward national rates, reaching equality by 2020. The State of California projected that state-level survival rates would converge toward the 2050 national-level survival rates published by the Census Bureau (State of California 2012). As we show in the next section, the targeting approach is often used in combination with trend extrapolation techniques.

4.3.3 Trend Extrapolation

Mortality and survival rates can also be projected by extrapolating historical trends. One practitioner of this approach is the Office of the Actuary in the Social Security Administration (SSA), which has been projecting U.S. mortality and survival rates since the 1930s. Initially, SSA projections accounted only for differences in mortality rates by age and sex; since the 1950s they have accounted for differences in the cause of death as well. In a recent set (Bell and Miller 2005), the SSA first calculated average annual rates of decline in mortality rates between 1981 and 2001 for each age/sex/cause-of-death group; if the mortality rate increased during that period for a particular group, that group's rate was projected to decline at a rate equal to 75% of the average decline for all groups. These rates of decline were projected to continue unabated for the first 2 years in the projection horizon, but were then projected to start converging toward target rates of decline, reaching those rates by 2029. After 2029, rates of decline in mortality rates for each age/sex/cause-of-death group were projected to remain constant. Assumptions regarding the target rates of decline were based on expectations regarding the development of new diagnostic and surgical techniques, changes in the prevalence of environmental pollutants, changes in lifestyle (e.g., nutrition and exercise), and similar factors.

The Census Bureau also uses extrapolation techniques to make projections of mortality and survival rates by age, sex, race, and ethnicity. In a set of national projections, Day (1996) extrapolated 1980–1990 trends in survival rates into the future, with adjustments to account for the impact of AIDS and several constraints imposed on the resulting rates. More recent sets of national projections have also extrapolated recent trends, but have projected that mortality rates will converge toward a set of survival rates based on expert judgment (Hollmann et al. 2000; U. S. Census Bureau 2008, 2012).

Extrapolation techniques assume that the future will be similar to the past in several important ways. This is not always a valid assumption. U.S. mortality rates declined continuously throughout the twentieth century, but the pace of those declines varied considerably. Rates of decline were fairly modest from 1900 to the mid-1930s, much larger from the mid-1930s to the mid-1950s, considerably smaller from the mid-1950s to the late 1960s, larger again from the late 1960s to the early 1980s, and smaller throughout the 1980s and 1990s (Bell and Miller 2005). Simple extrapolation techniques cannot pick up the timing and magnitude of changes such as these.

A more sophisticated type of extrapolation technique attempts to capture some of these changes through the use of time series models (Alders et al. 2007; Hyndman and Booth 2008; Lee and Carter 1992; McNown and Rogers 1989; Shang 2012; Torri and Vaupel 2012). Time series models account for changing trends over time and provide probabilistic prediction intervals for each projection. However, they require a high level of modeling expertise and have limited applicability to small areas due to the lack of reliable data and the high degree of variability in small-area mortality rates. In addition, projected changes tend to level off or converge to constant oscillations within a relatively short period (Land 1986). Time series models are used much more frequently for national projections than for state and local projections.

4.3.4 Cause-Delay

Cause-delay models focus on the implications of delaying (or completely eliminating) the occurrence of one or more causes of death (Manton et al. 1980; Olshansky 1987). The basic premise behind this approach is that changes in lifestyle and medical technology have delayed the occurrence of various types of deaths until progressively older ages. Consequently, as time goes by each cohort faces smaller mortality risks at each age than did the previous cohort.

Cause-delay models are often operationalized by assuming that cause-specific mortality rates for one age group in a population will gradually move toward those currently found in a younger age group in the same population (e.g., rates for 60–64 year olds will eventually become the same as those currently found for 55–59 year olds). The impact of such changes can be substantial. One application of a cause-delay model, for example, found that delaying cancer mortality rates by 10 years raised life expectancy at birth by 1.3 years for white males. The complete elimination of cancer as a cause of death, however, raised life expectancy at birth by only one additional year (Manton et al. 1980).

Cause-delay models are similar to targeting models in that one set of mortality rates gradually converges toward another. They differ in that the target population in cause-delay models is a younger cohort in the same population rather than the same cohort in a different population. An advantage of cause-delay models compared to targeting models is that by staying within the same population, cause-delay models control for many factors that cause mortality rates to differ from one population to another. The primary issue in applying cause-delay models is deciding what causes of death to focus on and how rapidly mortality rates for one cohort will move toward those currently found in another cohort. To our knowledge, cause-delay models have not been used in the preparation of official population projections in the United States.

4.3.5 Synthetic Projection

Synthetic mortality or survival rates can be created by linking changes in rates for one area to changes projected for a different area. This approach is similar to targeting, but it adopts the *rates of change* in mortality or survival rates from the model population rather than the rates themselves. This is a simple, straightforward approach that is used frequently for state and local projections (Campbell 1996; Department of Rural Sociology 1998; Smith and Rayer 2012; Treadway 1997).

Suppose that the middle series of the Census Bureau's national projections is accepted as a reasonable model of future changes in mortality rates by age, sex, race, and ethnicity in New Jersey. Projected changes in national rates could then be used to guide projected changes in New Jersey. For example, if survival rates for females aged 70–74 in the national population were projected to increase by 1.2% over the next 10 years, the same percent increase could be applied to survival rates for females aged 70–74 in New Jersey. This procedure can be carried out for every subgroup of the population, providing a complete set of projected survival rates.

The synthetic approach can be applied using either survival rates or mortality rates. However, in order to ensure that projected survival rates do not take on values greater than 1.0, survival rates are often converted into mortality rates before the adjustments are made (Shryock and Siegel 1973, p. 453). The procedure is as follows:

1. Mortality rates are calculated by subtracting survival rates from 1.0.
2. Adjustments to the mortality rates are made based on the changes projected for the model population.
3. Mortality rates are converted back into survival rates by subtracting the adjusted rates from 1.0.

Regardless of whether mortality or survival rates are used, the analyst must make sure the projected rates are reasonable. If survival/mortality rates for the model population are similar to those for the region being projected, the synthetic approach will generally produce reasonable results (at least for short- and medium-range projection horizons). If the rates are considerably different, however, changes in the model population may overstate or understate likely future changes in the population being projected. In these instances, further adjustments must be made or a different approach used.

4.3.6 *Expert Judgment*

Many analysts base projections of mortality rates on their own judgment regarding likely future trends. In fact, all the approaches described above require the use of the analyst's judgment as well as the application of the technique itself. Expert judgment is typically informed by the evaluation of current mortality rates, past mortality trends, and various socioeconomic, life style, medical, and technological factors that might cause mortality rates to change in the future. Taking this approach even further, projections can be based *solely* on expert judgment by gathering data from a panel of experts and forming probabilistic projections (Lutz et al. 1999). Data from a panel of experts can also be used in conjunction with one or more of the objective techniques described above (Alders et al. 2007).

4.4 Implementing the Mortality Component

We have described the construction of mortality and survival rates and several techniques that can be used to project those rates into the future. Where can the analyst find a set of survival rates for a particular area? Which technique (or techniques) should be used to project those rates into the future? How can those techniques best be applied? What can be done if no current data can be found? We offer the following suggestions for implementing the mortality component of the cohort-component method.

4.4.1 *Sources of Data*

National life tables have been published annually since 1945 by the NCHS (Arias 2011) and several times each decade by the SSA (Bell and Miller 2005). In addition, the NCHS has published life tables for states in conjunction with every decennial census since 1930 (National Center for Health Statistics 2012). The NCHS does not construct life tables for counties, but provides the data needed to construct such tables upon request. It should be noted, however, that small population sizes, missing data, and variations in data quality create special problems for county life tables. The data needed to construct reliable life tables for subcounty areas are virtually never available.

Must the analyst construct a new set of life tables if none are available for the areas to be projected? Fortunately, this is rarely necessary. Large regional differences in age-sex-race-specific mortality rates have mostly disappeared in the United States. Table 4.3 shows life expectancy at birth by race and sex for each state in 1999–2001. This is a handy way to summarize a population's age-specific mortality patterns. Although some differences can be seen, they are generally small, especially when compared to state-to-state differences in fertility and migration rates (as shown in the next two chapters).

Table 4.3 Life expectancy at birth by sex, United States and each state, 1999–2001

	White females	White males	Black females	Black males
Northeast				
Connecticut	81.9	76.7	77.7	71.7
Maine	80.9	75.6	*	*
Massachusetts	81.6	76.4	79.3	73.1
New Hampshire	81.3	76.5	*	*
New Jersey	81.3	75.8	75.5	68.9
New York	81.5	75.8	77.8	70.1
Pennsylvania	80.7	75.0	75.3	67.3
Rhode Island	81.6	76.1	77.4	72.2
Vermont	80.9	76.3	*	*
Midwest				
Illinois	80.8	75.3	74.2	66.8
Indiana	80.0	74.2	76.6	67.5
Iowa	81.4	76.2	75.2	70.8
Kansas	81.0	75.5	75.0	68.5
Michigan	80.6	75.3	76.0	67.4
Minnesota	82.6	77.0	76.6	71.6
Missouri	79.9	74.3	74.5	67.2
Nebraska	81.1	76.1	74.7	69.2
North Dakota	82.7	76.7	*	*
Ohio	80.0	74.6	74.9	68.6
South Dakota	82.6	76.4	*	*
Wisconsin	81.9	76.1	74.3	68.4
South				
Alabama	79.1	72.9	74.9	66.4
Arkansas	79.6	73.2	73.6	67.3
Delaware	80.6	75.2	72.9	70.3
District of Columbia	84.3	78.9	74.5	64.6
Florida	82.1	75.6	75.5	69.0
Georgia	79.5	73.9	76.2	68.3
Kentucky	78.4	72.7	74.5	69.0
Louisiana	79.4	73.5	75.3	66.5
Maryland	80.7	75.6	75.8	68.4
Mississippi	79.1	72.3	73.7	66.7
North Carolina	80.3	74.3	76.7	66.3
Oklahoma	78.8	73.0	74.3	69.0
South Carolina	80.0	73.8	75.4	67.3
Tennessee	79.3	73.3	74.2	66.9
Texas	80.4	74.7	74.8	69.2
Virginia	80.7	75.6	76.2	69.4
West Virginia	78.4	72.8	72.7	69.9

(continued)

Table 4.3 (continued)

	White females	White males	Black females	Black males
West				
Alaska	80.1	75.4	*	*
Arizona	81.6	75.5	77.7	71.0
California	81.4	76.1	76.7	70.0
Colorado	81.3	76.2	76.6	71.7
Hawaii	83.3	78.4	*	*
Idaho	80.5	76.5	*	*
Montana	81.2	75.1	*	*
Nevada	79.0	73.5	74.8	70.6
New Mexico	80.7	75.2	74.4	71.6
Oregon	80.2	75.7	78.2	70.7
Utah	80.9	77.0	*	*
Washington	80.0	76.1	77.1	71.9
Wyoming	80.4	75.3	*	*
United States	80.0	74.8	75.2	68.2

Source: National Center for Health Statistics, United States Decennial Life Table*s*, 1999–2001: State Life Tables. http://www.cdc.gov/nchs/nvss/mortality/lewk4.htm

*Indicates that figure does not meet standards of reliability or precision (based on fewer than 20 cases)

Because survival rates for many areas in the United States are similar, proxy rates from a different area can generally be used for areas for which no life tables have been constructed (e.g., state life tables can be used for county projections). However, it is important to choose a model population with characteristics similar to those of the area to be projected. If the population has large numbers of racial or ethnic minorities with substantially different survival rates, it is advisable to make separate projections for each racial/ethnic group or to construct survival rates weighted by race and ethnicity. Applying proxy survival rates to the region's population in a recent year and comparing the resulting number of deaths with the number actually occurring provides a test of the validity of the proxy rates.

Life tables based on small-area mortality and population data could be constructed, of course. However, we believe the costs of constructing those tables—combined with problems of data reliability—generally outweigh the benefits. Furthermore, other types of errors typically swamp errors caused by the use of proxy survival rates. We believe scarce resources can be better spent elsewhere. (One exception may be places with unique population or mortality characteristics, for which no reliable proxy rates can be found).

4.4.2 Views of the Future

Once a set of base survival rates has been chosen, the next step is to decide how to project those rates into the future. Given the wide range of methods that can be used, how can the analyst choose the one(s) that will be most appropriate for a particular set of projections? This choice will be determined partly by the availability of relevant data but will also be affected by the analyst's views regarding future mortality trends.

Demographers, scientists, physicians, and healthcare experts are sharply divided in their views of future mortality trends. One group of researchers believes it is unlikely that life expectancy at birth will increase a great deal beyond the levels currently found in low-mortality countries (Carnes and Olshansky 2007; Fries 1980, 1989; Olshansky et al. 1990). They point to the finite number of cell doublings in a life span, the steady loss of organ capacity that begins around age 30 in human beings, the much smaller increases in life expectancy occurring at older ages than younger ages during the twentieth century, the failure of many people to adopt lifestyle habits known to increase health and longevity, and the relatively modest increases in life expectancy that would be implied by even the total elimination of several leading causes of death. Many researchers in this group believe life expectancy at birth is likely to level off around age 85; some even speculate that it might decline from current levels (Olshansky et al. 2005).

Another group of researchers believes considerably larger gains in life expectancy are possible (Ahlburg and Vaupel 1990; Fogel and Costa 1997; Manton et al. 1991; Torri and Vaupel 2012). They point to the technological and biomedical advances that have already occurred and to the likelihood of further breakthroughs, an increased awareness of the benefits of healthy lifestyles (e.g., reduced smoking, improved nutrition, increased exercise), increased access to healthcare services, the high life expectancies already found in several population subgroups that practice healthy lifestyles and have access to good medical care, the persistence of mortality declines throughout the twentieth century, and the tendency for past forecasts to understate future increases in longevity. These researchers see life expectancies at birth rising to 95, 100, or even higher by the end of the current century. Indeed, Vaupel (2010) suggests that half of the children alive today in countries with high life expectancies may live to be 100.

The Census Bureau and SSA are the two main sources of national population projections in the United States. Both agencies project mortality rates using a combination of extrapolation techniques and the application of expert judgment. In recent projections, the Census Bureau projected life expectancy at birth to rise from 76 to 81 between 2010 and 2050 for males and from 81 to 85 for females (U. S. Census Bureau 2008). Over the same period, the SSA projected increases to 80 and 84 for males and females, respectively (Social Security Administration 2012).

Ahlburg and Vaupel (1990) presented two alternative extrapolation scenarios, one based on the continuation of 2% annual reductions in mortality rates at each age and the other based on the continuation of 1% annual reductions. Both scenarios are consistent with trends occurring in the United States at particular times during the twentieth century. The first scenario produced life expectancies at birth of 100 for females and 96 for males in 2080; the second produced life expectancies of 89 and 84, respectively. The second scenario is similar to the ARIMA time series forecasts produced by Lee and Tuljapurkar (1994), which showed a life expectancy at birth (both sexes) of 86 in 2065, with a predicted range of 81–90.

When the purpose of projecting is to *forecast* the future population, the analyst who anticipates only modest improvements in longevity may want to apply assumptions similar to those used by the Census Bureau or the SSA. Conversely, one who anticipates larger increases in life expectancy might favor assumptions similar to Ahlburg & Vaupel's rapid-reduction scenario. When the purpose of projecting is simply to *illustrate* or *analyze*, these contrasting projections provide an opportunity to explore the implications of alternative mortality scenarios.

4.4.3 Examples

The following examples illustrate two of the methods that can be used to project future mortality. Both are from Florida, where demographers use a synthetic approach tying projected changes in state survival rates to projected changes in national survival rates (Smith and Rayer 2012). The starting point in these projections was a set of 5-year survival rates by age and sex, based on Florida life tables for 1999–2001. These survival rates were adjusted upward at 10-year intervals, based on adjustment factors derived from projected changes in U.S. survival rates through 2050 (Hollmann et al. 2000, including unpublished data available on the Census Bureau web site).

Adjustment factors (${}_5A_x$) were calculated for each age-sex group by forming ratios of survival rates in projected year t + 10 to survival rates in year t:

$${}_5\mathrm{A}_\mathrm{x} = {}_5\mathrm{S}_{\mathrm{x,t+10}} / {}_5\mathrm{S}_{\mathrm{x,t}}$$

where ${}_5S_{x,t+10}$ is the 5-year U.S. survival rate for age group x to $x + 5$ in year $t + 10$ and ${}_5S_{x,t}$ is the 5-year survival rate for age group x to $x + 5$ in year t. For example, the 5-year national survival rate for males aged 50–54 was 0.96106 in 2000 and was projected to be 0.96500 in 2010. The adjustment factor for males aged 50–54 is calculated as:

$${}_5\mathrm{S}_{50,2010} / {}_5\mathrm{S}_{50,2000} = 0.96500/0.96106 = 1.00410$$

Similar adjustment factors were calculated for males and females in each 5-year age group through 80+. These adjustment factors were then multiplied by the 2000 Florida survival rates to give projected survival rates in 2010.

Table 4.4 shows 2000 survival rates, adjustment factors, and projected 2010 survival rates for males in Florida. Adjustments were also made for 2020, 2030, and 2040, the last year in the projection horizon. Survival rates for mid-decade years (2015, 2025, and 2035) were made by interpolating between beginning-of-decade and end-of-decade rates. The mortality assumption used in Florida, then, was that the state's age-sex-specific survival rates would change at the same rate as the corresponding rates for the nation as a whole.

Table 4.4 Projected 2010 survival rates for Florida males, based on projected United States survival rates

Age	2000 survival rate	U.S. adjustment factor	2010 survival rate[a]
0–1	0.99146	1.00080	0.99225
1–4	0.99806	1.00017	0.99823
5–9	0.99891	1.00015	0.99906
10–14	0.99698	1.00026	0.99724
15–19	0.99378	1.00053	0.99431
20–24	0.99251	1.00041	0.99292
25–29	0.99202	1.00024	0.99226
30–34	0.98965	1.00053	0.99017
35–39	0.98511	1.00100	0.98610
40–44	0.97782	1.00184	0.97962
45–49	0.96898	1.00285	0.97174
50–54	0.95701	1.00410	0.96093
55–59	0.93941	1.00661	0.94562
60–64	0.91571	1.01001	0.92488
65–69	0.87969	1.01517	0.89303
70–74	0.82405	1.02483	0.84451
75–79	0.74043	1.03953	0.76970
80+	0.51176	1.05641	0.54063

Sources: Florida Department of Health Office of Vital Statistics, Unpublished Abridged Life Tables, 1999–2001

U.S. Census Bureau, Population projections of the United States by age, sex, race, Hispanic origin, and nativity: 1999–2100. (NP-D5) Component assumptions of the resident population by age, sex, race, and Hispanic origin: Lowest, middle, and highest series, 1999–2100. Internet Release Date: May 2000

[a]2000 survival rate $\times$ adjustment factor

All the adjustment factors shown in Table 4.4 were above 1.0, indicating that survival rates were projected to increase for every age group. The increases were far from uniform, however. Adjustments were smallest in the 5–9 age group (1.00015) and generally increased with age thereafter, reaching 1.05641 for the oldest group. This pattern reflects the fact that survival rates are already very high at the younger ages, leaving those groups with little potential for further improvements.

The same Florida data can be used to illustrate another projection method. Ahlburg and Vaupel (1990) made two sets of extrapolations, one based on 1% annual reductions in age-specific mortality rates and the other based on 2% annual reductions. We applied 1% annual reductions to 2000 mortality rates for males in Florida to create projected rates for 2010 (Table 4.5). The first column shows 2000 survival rates; these are the same rates shown in the first column of Table 4.4. The second column shows the mortality rates obtained by subtracting each survival rate from 1.0. The third column shows the adjusted mortality rates for 2000 after 1% annual reductions have been applied to the mortality rates shown in Column 2. The fourth column shows the new survival rates implied by the adjusted mortality rates.

The 2010 survival rates shown in Table 4.5 are very similar to those shown in Table 4.4. That is, the increases in survival rates projected by the Census Bureau

Table 4.5 Projected 2010 survival rates for Florida males, based on 1% annual declines in mortality rates[a]

Age	2000 survival rate	2000 mortality rate[b]	2010 mortality rate[c]	2010 survival rate[d]
0–1	0.99146	0.00854	0.00772	0.99228
1–4	0.99806	0.00194	0.00175	0.99825
5–9	0.99891	0.00109	0.00099	0.99901
10–14	0.99698	0.00302	0.00273	0.99727
15–19	0.99378	0.00622	0.00563	0.99437
20–24	0.99251	0.00749	0.00677	0.99323
25–29	0.99202	0.00798	0.00722	0.99278
30–34	0.98965	0.01035	0.00936	0.99064
35–39	0.98511	0.01489	0.01347	0.98653
40–44	0.97782	0.02218	0.02006	0.97994
45–49	0.96898	0.03102	0.02805	0.97195
50–54	0.95701	0.04299	0.03888	0.96112
55–59	0.93941	0.06059	0.05480	0.94520
60–64	0.91571	0.08429	0.07623	0.92377
65–69	0.87969	0.12031	0.10881	0.89119
70–74	0.82405	0.17595	0.15913	0.84087
75–79	0.74043	0.25957	0.23475	0.76525
80+	0.51176	0.48824	0.44155	0.55845

Source: Florida Department of Health, Office of Vital Statistics, Unpublished Unabridged Life tables, 1999–2001

[a]1% annual decline in mortality for 10 years is represented by an adjustment factor of 0.90438 (i.e., 0.99^{10})

[b]1 − 2000 survival rate

[c]2000 mortality rate × 0.90438

[d]1 − 2010 mortality rate

were very close to those coming from a decline of 1% per year in mortality rates. In general, differences in projection methodologies will not lead to large differences in survival rates unless the projections are based on dramatically different assumptions or extend well into the future.

4.5 Conclusions

We have looked at a number of ways to project survival rates based on different techniques, assumptions, and perspectives regarding future mortality trends. How sensitive are population projections to these differences? How important is the mortality component to the production of cohort-component population projections?

In terms of its impact on total population size, the choice of mortality rates is not very important, especially for short- and medium-range projections (i.e., less than 20 years). Long (1989) reported that for 20-year national projections, the population projected under the high mortality assumption was only 1.0% below that projected under the medium assumption; the population projected under the low mortality assumption was only 1.3% above the medium projection. Even for a 50-year horizon, the total population projected under the high mortality assumption was only 3% smaller than that projected under the medium assumption; the low mortality assumption led to a population only 4% larger.

The impact of differences in mortality assumptions on projections of total population may be somewhat larger at the state and local levels than at the national level. States and local areas exhibit some variability in age-sex-specific mortality rates, even after accounting for differences in race (Isserman 1993). They also have the potential for larger changes in mortality rates in the future than would be expected at the national level because the potential for changes in socioeconomic and demographic characteristics is greater for states and local areas than it is for the nation as a whole. However, a study of 30-year projections for 55 counties in West Virginia found that using state mortality rates instead of county-specific rates led to differences in total population that averaged only 1% (Isserman 1993). In general, reasonable differences in mortality assumptions will have relatively little impact on state and local projections of total population, even for fairly long-range projections.

Differences in mortality rates among states and local areas are much smaller than differences in fertility and migration rates (Smith and Ahmed 1990). In addition, mortality rates change more slowly and consistently over time than fertility and migration rates, making them easier to forecast accurately. As a result, differences in mortality assumptions generally have much less impact on projections of total population than do differences in fertility and migration assumptions.

For projections of the older population, however, differences in mortality rates can have a substantial impact. Mortality rates for young and middle-aged persons in the United States are already so low that there is little room left for further improvement. Indeed, it has been estimated that eliminating *all* deaths below age 50 would increase life expectancy at birth by only 3.5 years (Olshansky et al. 1990). Among older age groups, however, mortality rates are considerably higher, leaving more room for improvement and creating more possibilities for differences in projected rates.

This can be illustrated by comparing two sets of projections from the SSA. Projections made in 1974 showed only 31.0 million persons aged 65+ in the year 2000, whereas projections made in 1984 showed 36.2 million. This increase of more than five million was caused by changes in mortality assumptions for the elderly population; it accounted for about 80% of the 6.4 million increase projected for the total population (Olshansky 1988). Differences in projected mortality rates clearly have more impact on the elderly population than on the population as a whole.

Projections of the older population are particularly important for analyses of healthcare, disability, housing, transportation, and entitlement programs like Social Security and Medicare (Bennett and Olshansky 1996; Fogel and Costa 1997; Martin et al. 2010; Rogers 1995; Smith et al. 2008). Does greater longevity lead to more years of healthy living or simply to longer periods of illness, disability, and institutionalization? What are the connections between changes in mortality rates and changes in health status? How does population aging affect transportation and housing needs? What are the fiscal implications of an aging population? These are hotly debated questions with tremendous social, economic, and ethical implications. Although decisions regarding mortality assumptions have a modest impact on projections of total population for most states and local areas in the United States, they are very important for other reasons.

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Chapter 5
Fertility

The term *fertility* refers to the occurrence of a live birth (or births) to an individual, a group, or an entire population. It is determined by a combination of biological, social, psychological, economic, and cultural factors. Biological factors affect *fecundity* (i.e., the physiological capacity to reproduce), whereas social, psychological, economic, and cultural factors affect choices regarding whether to have children, how many to have, and when to have them. Although biological factors set an upper limit on a woman's lifetime fertility, most women bear children at levels far below that limit. The broad array of factors affecting personal choices is thus paramount in the study of fertility.

Fertility rates vary considerably among individuals and populations. Some women have no children, others have one or two, and some have 10 or more. At current rates American women will average about two births during their lifetimes. This is considerably higher than the rates of 1.4 or fewer births per women found in Japan, South Korea, Germany, Italy, Spain, and several other Asian and European countries, but is much lower than the rates of 6.0 or higher found in Afghanistan, Mali, Niger, Uganda, Zambia, and several other African countries (Population Reference Bureau 2011). According to the Guinness World Records, the most prolific mother ever was a Russian woman in the eighteenth century who was reported to have borne 69 children through 27 pregnancies (Weeks 2012, p. 200).

Fertility rates change over time, sometimes rising and sometimes falling. During colonial times, women in the United States averaged around eight births during their lifetimes (Weeks 2012, p. 250). Fertility rates fell rapidly during the nineteenth and early twentieth centuries, reaching levels below 2.3 during the 1930s. The baby boom raised them above 3.7 by the late 1950s but the baby bust dropped them below 1.8 by the mid-1970s, their lowest levels ever. Rates rose to 2.1 in 2006 and 2007 but have since fallen below 2.0. Economic downturns—such as the severe recession gripping the United States from 2007 to 2009—have often been found to cause short-term declines in fertility rates (Sobotka et al. 2011). Figure 5.1 shows total fertility rates in the United States from 1920 to 2010.

Whereas mortality rates fell relatively slowly and steadily during the twentieth century, fertility rates fluctuated substantially, often within a relatively short time.

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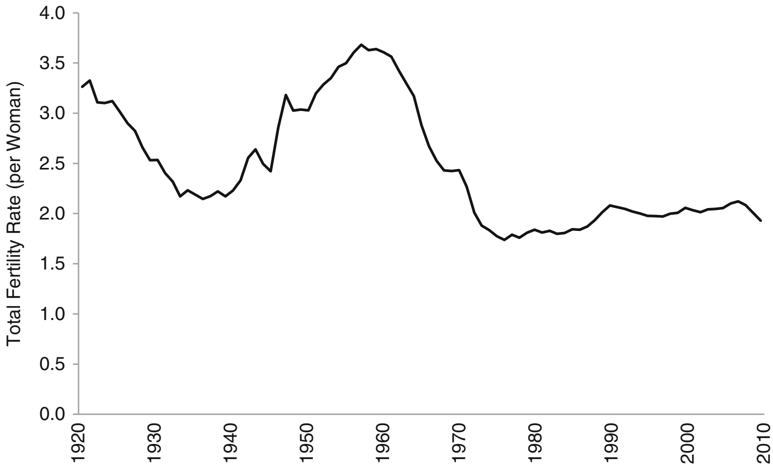

Fig. 5.1 Total fertility rates, United States, 1920–2010 (Sources: National Center for Health Statistics (1976, 2011))

These wide swings make it more difficult to construct accurate forecasts of fertility rates than mortality rates. In this chapter we describe several fertility measures and discuss two different perspectives from which fertility behavior can be viewed, one focusing on births during a particular period of time (e.g., 1 year) and the other focusing on the cumulative fertility behavior of a particular cohort of women as they pass through their childbearing years. We describe a number of approaches to projecting fertility rates and discuss sources of fertility data. Again, we pay special attention to the problems of making projections for small areas. We close with an assessment of the impact of fertility assumptions on population projections.

5.1 Fertility Measures

A number of measures have been developed to reflect fertility behavior. In this section, we describe several of the most commonly used measures. All are based on two types of data: the number of live births occurring in a geographic area during a particular period (hereinafter referred to simply as births) and the population of that area. These measures are called *birth* (or *fertility*) *rates* because they relate the number of births to the population exposed to the risk of giving birth. However, as discussed in Chap. 2, they are not rates in a true probabilistic sense.

Fertility rates typically refer to a calendar year. The numerator is the number of births occurring during the year and the denominator is the midyear population. Sometimes a 3-year average of births is used to smooth out the effects of annual fluctuations; this is particularly important for areas with small populations. Some measures use data for the entire population, while others focus on particular population subgroups. Birth data in the United States are collected by the vital statistics agencies of each state and are compiled nationally by the National Center for Health Statistics (NCHS). Population data are based on census counts or estimates, depending on the year(s) for which the rates are to be constructed.

5.1.1 Crude Birth Rate

The simplest fertility measure is the crude birth rate (CBR), which is calculated by dividing the number of births during a year by the midyear population. It is generally multiplied by 1,000 to reflect the number of births per 1,000 persons:

$$\mathrm{CBR} = (\mathrm{B/P})\ (1{,}000)$$

where B is the number of births during the year and P is the midyear population. For example, there were 4,000,279 births in the United States in 2010 and a midyear population of 309,349,689, yielding a CBR of:

$$(4,000,279/309,349,689)\ (1{,}000) = 12.9$$

That is, there were 12.9 births for every 1,000 residents of the United States in 2010. For states, CBRs in 2010 ranged from 9.8 in Maine and New Hampshire to 18.9 in Utah (Hamilton et al. 2011).

Crude birth rates can also be calculated for different racial or ethnic groups and for different geographic regions. For example, there were 946,000 births to persons of Hispanic origin in the United States in 2010 and a midyear population of 50,810,213, yielding a CBR of:

$$(946,000/50,810,213)\ (1{,}000) = 18.6$$

That is, there were 18.6 births for every 1,000 persons of Hispanic origin residing in the United States in 2010.

The usefulness of the CBR as a measure of fertility is limited because it does not account for differences in demographic characteristics. Births occur only to females, primarily those between the ages of 15 and 44. The age-sex structure of a population thus has a major impact on its fertility behavior. Other fertility measures have been developed to account for differences in age and sex characteristics.

5.1.2 General Fertility Rate

The general fertility rate (GFR) relates the number of births to the number of females in their prime childbearing years. It is calculated by dividing the number of births by the number of females aged 15–44. It is typically expressed in terms of births per 1,000:

$$\mathrm{GFR} = (\mathrm{B}/\mathrm{F}_{15-44})\ (1{,}000)$$

where $F_{15\text{-}44}$ is the midyear population of females aged 15–44. For example, there were 4,000,279 births in the United States in 2010 and 62,401,146 women aged 15–44, yielding a general fertility rate of:

$$(4{,}000{,}279/62{,}401{,}146)\ (1{,}000) = 64.1$$

GFRs can be calculated for different racial and ethnic groups and for different geographic regions. For example, the GFR for Hispanic women in the United States in 2010 was 80.3, compared to 58.7 for non-Hispanic whites and 66.6 for non-Hispanic blacks. For states, GFRs ranged from 51.4 in New Hampshire to 86.7 in Utah (Hamilton et al. 2011).

The GFR (sometimes simply called the *fertility rate*) provides a more refined measure than the CBR because it relates the number of births to the population most likely to give birth. It has several shortcomings, however. Some births occur to women younger than 15 or older than 44. More important, the distribution of persons *within* the ages of 15–44 differs from one population to another and changes over time. A third measure accounts for these differences by focusing on birth rates for each individual age group.

5.1.3 Age-Specific Birth Rate

The age-specific birth rate (ASBR) is calculated by dividing the number of births to females in a given age group by the number of females in that age group. It is typically multiplied by 1,000 to reflect the number of births per 1,000 females:

$${}_{\mathrm{n}}\mathrm{ASBR}_{\mathrm{x}} = ({}_{\mathrm{n}}\mathrm{B}_{\mathrm{x}}/{}_{\mathrm{n}}\mathrm{F}_{\mathrm{x}})\ (1{,}000)$$

where x is the youngest age in the age interval, n is the number of years in the age interval, ${}_nB_x$ is the number of births to females between the ages of x and $x + n$, and ${}_nF_x$ is the number of females between the ages of x and $x + n$. Rates can be calculated by single year of age, but are more commonly expressed in 5-year age groups. For example, there were 951,900 births to females aged 20–24 in the United States in 2010 and a midyear population of 10,611,599, yielding an ASBR of:

$${}_{5}\mathrm{ASBR}_{20} = (951{,}900/10{,}611{,}599)\ (1{,}000) = 89.7$$

Table 5.1 shows ASBRs for the United States in 2010. Several things stand out. First, ASBRs were very low for women younger than age 15 or older than age 44.

Table 5.1 Age-specific birth rates, United States, 2010

Age	Births	Female population	ASBR[a]
10–14	4,500	10,106,622	0.4
15–19	367,752	10,696,317	34.4
20–24	951,900	10,611,599	89.7
25–29	1,134,008	10,477,448	108.2
30–34	962,420	10,030,407	96.0
35–39	464,943	10,085,603	46.1
40–44	107,011	10,499,772	10.2
45–49	7,744	11,465,341	0.7
U.S. total	4,000,278	83,973,109	

Sources: Hamilton et al. (2011), U. S. Census Bureau (2011)
[a]Births / female population × 1,000

Women in these two age groups accounted for less than 1% of all births, making 15–44 a reasonable choice for the denominator in the GFR. Second, ASBRs for women in their twenties and early thirties were much higher than for women in any other age group. This is not surprising, of course, and is a pattern found throughout the world.

Because birth rates vary so much by age, focusing on ASBRs yields a great deal of useful information. However, all this detail makes it difficult to evaluate changes in fertility behavior over time and to compare differences among regions. The next measure summarizes the entire array of ASBRs and facilitates such comparisons.

5.1.4 Total Fertility Rate

The total fertility rate (TFR) is the sum of all the individual ASBRs. When ASBRs are computed for 1-year age groups, the TFR is calculated as:

$$\mathrm{TFR} = \sum \mathrm{ASBR_x}$$

When age groups are defined in 5-year intervals, the TFR is calculated by multiplying the sum of the ASBRs by 5 (to account for the fact that females spend 5 years in each age group):

$$\mathrm{TFR} = 5\sum {}_5\mathrm{ASBR_x}$$

Total fertility rates based on 5-year age groups are generally about the same as those based on 1-year age groups (Shryock and Siegel 1973, p. 484).

The TFR can be interpreted as the number of children a hypothetical cohort of 1,000 women would have during their lifetimes if none died and their fertility behavior at each age conformed to a given set of ASBRs. Using the data from Table 5.1, we can calculate the TFR for the United States in 2010 as:

$$\mathrm{TFR} = 5\ (0.4 + 34.4 + 89.7 + 108.2 + 96.0 + 46.1 + 10.2 + 0.7) = 1{,}929$$

TFRs are often expressed as the average number of births per woman, rather than as the total number of births per 1,000 women. Using the example shown above, women just entering their childbearing years in 2010 would have an average of 1.93 births by the time they stopped having children, if none died and 2010 ASBRs remained constant.

The TFR is similar to life expectancy at birth (e_0) in that both measures use hypothetical cohorts and both assume that a given set of age-specific rates will continue indefinitely. One measure shows the average number of children a cohort of women would have if a given set of ASBRs persisted throughout their lifetimes. The other shows the average length of life a cohort of newborn babies would have if a given set of ASDRs persisted throughout their lifetimes. Because they have clear intuitive meanings and are unaffected by the age-sex structure of a population, both measures are useful for making comparisons among regions and over time.

Further refinements to these measures can be made. The gross reproduction rate (GRR) is similar to the TFR but focuses on female births rather than total births. The net reproduction rate (NRR) adjusts the GRR to account for survival rates at each age. These measures are useful for many analytical purposes but are not commonly used for population projections. Discussions of these and other fertility measures can be found in Newell (1988), Estee (2004), and Smith (1992).

5.1.5 Child-Woman Ratio

A final measure sometimes used when making population projections is the child-woman ratio (CWR):

$$\mathrm{CWR} = (\mathrm{P}_{0-4}/\mathrm{F}_{15-44})\ (1{,}000)$$

where $P_{0\text{-}4}$ is the number of children aged 0–4 and $F_{15\text{-}44}$ is the number of women aged 15–44. For example, there were 69,520 children aged 0–4 in Maine in 2010, and 241,923 women aged 15–44, yielding a CWR of 69,520 / 241,923 = 0.2874, or 287 children for every 1,000 women aged 15–44. In Utah, the CWR was 263,924 / 623,651 = 0.4232, or 423 children for every 1,000 women aged 15–44.

The CWR is neither a rate nor a true fertility measure. It is simply a ratio of one population subgroup to another. It incorporates the effects of past mortality and migration patterns as well as past fertility behavior. In contrast to most fertility measures, it does not require any data specifically related to births. This is a major shortcoming for many analytical purposes, but it can be useful for geographic areas lacking vital statistics data. The CWR ratio is often used in analyses of less developed countries. As we show in Chap. 7, it can also be used in more developed countries for projections of small areas lacking birth data.

5.2 Two Perspectives: Period and Cohort

Fertility can be viewed from two perspectives, each useful for particular purposes. The period perspective is cross-sectional, focusing on births during a particular time period (e.g., 1 year). All the fertility measures discussed above are period measures: CBR, GFR, ASBRs, and TFR are based on the number of births occurring during a year (or an average of several years) and the size of the midyear population. The cohort perspective, on the other hand, is longitudinal, focusing on the cumulative fertility behavior of a particular cohort of women (e.g., those born in 1960) as they pass through their childbearing years. Each perspective has its advantages and disadvantages and each has its proponents and critics. It is important to recognize the differences and similarities between these two perspectives before considering techniques for projecting fertility rates.

5.2.1 Defining the Relationship

Tables 5.2 and 5.3 illustrate the relationship between period and cohort fertility measures. Table 5.2 shows annual ASBRs and TFRs at 5-year intervals from 1940 to 2010 for women in the United States. The rows summarize age-specific fertility behavior for each year; the columns show the changes in ASBRs and TFRs over time. Looking across each row shows the typical relationship between ASBRs and age, with rates increasing from the teens to the twenties and declining thereafter. Looking down each column shows the large increases and declines in fertility rates that occurred during the baby boom and bust. Each row thus provides a snapshot of fertility behavior at a particular point, and comparing rows provides an indication of how those snapshots have changed over time.

A different picture emerges if we look at Table 5.2 diagonally instead of by rows and columns. Consider females born in 1925–1929. They were age 10–14 in 1940, 15–19 in 1945, 20–24 in 1950, and so forth. The ASBRs for this cohort were 0.7 at 10–14, 51.1 at 15–19, 196.6 at 20–24, and so forth. If we add up all these ASBRs, multiply by 5, and divide by 1,000, we get the cohort fertility rate (CFR):

$$\begin{aligned}\text{CFR} &= 5\,(0.7 + 51.1 + 196.6 + 190.5 + 112.7 + 46.2 + 8.1 + 0.3)/1,000 \\ &= 3.03\end{aligned}$$

The CFR calculated in this manner is sometimes called the *cumulative fertility rate* or *completed family size*. In contrast to the TFR, the CFR is a measure of the

Table 5.2 Age-specific birth rates and total fertility rates, United States, 1940–2010

Year	10–14	15–19	20–24	25–29	30–34	35–39	40–44	45–49	TFR[a]
1940	0.7	54.1	135.6	122.8	83.4	46.3	15.6	1.9	2.30
1945	0.8	51.1	138.9	132.2	100.2	56.9	16.6	1.6	2.49
1950	1.0	81.6	196.6	166.1	103.7	52.9	15.1	1.2	3.09
1955	0.9	90.5	242.0	190.5	116.2	58.7	16.1	1.0	3.58
1960	0.8	89.1	258.1	197.4	112.7	56.2	15.5	0.9	3.65
1965	0.8	70.5	195.3	161.6	94.4	46.2	12.8	0.8	2.91
1970	1.2	68.3	167.8	145.1	73.3	31.7	8.1	0.5	2.48
1975	1.3	55.6	113.0	108.2	52.3	19.5	4.6	0.3	1.77
1980	1.1	53.0	115.1	112.9	61.9	19.8	3.9	0.2	1.84
1985	1.2	51.0	108.3	111.0	69.1	24.0	4.0	0.2	1.84
1990	1.4	59.9	116.5	120.2	80.8	31.7	5.5	0.2	2.08
1995	1.3	56.8	109.8	112.2	82.5	34.3	6.6	0.3	2.02
2000	0.9	47.7	109.7	113.5	91.2	39.7	8.0	0.5	2.06
2005	0.7	40.4	102.2	115.5	95.8	46.3	9.1	0.6	2.05
2010	0.4	34.4	89.7	108.2	96.0	46.1	10.2	0.7	1.93

Sources: Hamilton et al. (2011), U. S. Census Bureau (1961, 1985, 2012b)
[a]5 × (Sum of the age-specific rates) / 1,000

actual fertility behavior of a real cohort of women over their lifetimes. Table 5.3 shows the ASBRs taken from the diagonals of Table 5.2 and the associated CFRs. Age groups 10–14 and 45–49 were excluded from this table because they account for such a tiny proportion of total births; excluding those groups allows us to increase the number of cohorts for which CFRs can be calculated.

The typical age pattern is found, with ASBRs increasing as women move from their teens to their twenties and declining as they move through their thirties and forties. The impact of the baby boom and bust is clearly evident, with CFRs rising for the first three birth cohorts (women who were in their twenties in the 1940s and 1950s) and declining for the following four cohorts (women who were in their twenties in the 1960s and 1970s).

It is noteworthy that the changes over time in the cohort fertility rates shown in Table 5.3 are considerably smaller than the changes in total fertility rates shown in Table 5.2. This is a common empirical finding and suggests that changes in period rates are caused partly by changes in the timing of births rather than solely by changes in completed family size (Frejka and Sobotka 2008; Ni Bhrolchain 2011; Van Imhoff 2001). A number of analysts have concluded that the low period fertility rates found in the United States during the 1970s and the even lower rates found in Europe during the 1990s were caused partly (some would say primarily) by the decisions of many women to delay childbearing until older ages (Bongaarts and Feeney 1998; Goldstein et al. 2009; Schoen 2004; Sobotka 2004).

This movement toward delayed childbearing in the United States can be seen in Table 5.2. Age-specific birth rates for women above age 30 have been rising steadily since 1980 while ASBRs rates have been falling or holding steady for women less than age 30. Between 1980 and 2010, ASBRs fell by 35%, 22%, and 4% for ages 15–19, 20–24, and 25–29, respectively, while rising by 55%, 133%, and 162% for ages 30–34, 35–39, and 40–44.

Table 5.3 Age-specific birth rates and cohort fertility rates, United States, birth cohorts 1920–1924 to 1965–1969

Year of birth	15–19	20–24	25–29	30–34	35–39	40–44	CFR[a]
1920–1924	54.1	138.9	166.1	116.2	56.2	12.8	2.72
1925–1929	51.1	196.6	190.5	112.7	46.2	8.1	3.03
1930–1934	81.6	242.0	197.4	94.4	31.7	4.6	3.26
1935–1939	90.5	258.1	161.6	73.3	19.5	3.9	3.03
1940–1944	89.1	195.3	145.1	52.3	19.8	4.0	2.53
1945–1949	70.5	167.8	108.2	61.9	24.0	5.5	2.19
1950–1954	68.3	113.0	112.9	69.1	31.7	6.6	2.01
1955–1959	55.6	115.1	111.0	80.8	34.3	8.0	2.02
1960–1964	53.0	108.3	120.2	82.5	39.7	9.1	2.06
1965–1969	51.0	116.5	112.2	91.2	46.3	10.2	2.14

Sources: Hamilton et al. (2011), U. S. Census Bureau (1961, 1985, 2012b)
[a]5 × (Sum of the age-specific rates) / 1,000

It is also noteworthy that TFRs and CFRs have been fairly similar and quite stable for the past 20 years. Total fertility rates ranged between 2.02 and 2.08 between 1990 and 2005. Cohort fertility rates for the 1950–1954, 1955–1959, and 1960–1964 birth cohorts—women who had largely completed their childbearing by 1995, 2000, and 2005, respectively—were virtually the same, ranging between 2.01 and 2.06. The trends diverged a bit between 2005 and 2010, when the TFR fell to 1.93— most likely because of a severe economic recession— while the CFR rose to 2.14. We discuss the implications of these findings for the construction of population projections later in this chapter.

5.2.2 Assessing the Issues

Which is better for studying fertility, the period perspective or the cohort perspective? Many believe the cohort perspective is better. According to Ryder (1965, 1986, 1990), the cohort perspective more accurately describes the sequential nature of childbearing than does the period perspective. Cohorts are socially and demographically distinct and their distinctiveness—including fertility attitudes and behavior—tends to persist over time. Most theories of fertility focus on completed family size rather than the timing of births. In addition, cohort measures change more smoothly over time than do period measures; this is generally considered to be an advantage. By focusing on the ASBRs of a particular cohort of women as they pass through their childbearing years, the cohort perspective picks up age, period, *and* cohort influences on fertility.

From the period perspective it is not clear whether year-to-year changes in fertility rates reflect changes in long-term fertility behavior or simply a shift in the timing of births. As an extreme example, consider the Year of the Fire Horse in Japan (Ni Bhrolchain 2011). Many people believed 1966 would be an inauspicious year for a girl to be born and the TFR dropped by 26% before bouncing back the following year. The dramatic drop in 1966 clearly reflected changes in the timing of births, not their ultimate number. Wars, economic recessions, and other events may cause similar (if less dramatic) short-term changes in the timing of births. These changes may have a substantial impact on period fertility measures but little or no impact on cohort measures.

Furthermore, more gradual but longer-lasting shifts in timing can cause period measures to persistently overstate changes in completed family size. For example, accelerated childbearing played an important role in the baby boom and delayed childbearing played an important role in the baby bust. In the United States, these timing shifts contributed to the rapid increase in period fertility rates during the 1940s and 1950s and their rapid decline during the 1960s and 1970s.

Proponents of the cohort perspective view cohorts as the vehicles of causation, while periods simply reflect the consequences of changes in cohort behavior. Under this view each birth cohort is unique, developing its own ideas, values, sentiments, vocabulary, and style as its members age together and experience the same events, institutions, economic conditions, and social norms at various stages of their lives. As an Arab proverb puts it, “Men resemble the times more than they do their fathers” (quoted in Ryder 1965, p. 853). Attitudes regarding sexuality, contraception, and ideal family size are strongly affected by “the times.”

Many studies of fertility behavior have been based on a cohort perspective (Bloom and Trussell 1984; Bongaarts 2002; Lesthaeghe and Surkyn 1988; Ryder 1986, 1990). Some focused on parity-progression ratios, or the proportions of women at each level of childbearing (e.g., no children, one child, two children) who go on have at least one more child. Others focused on changes in the length of the time interval between births. Some focused on marital fertility by combining marriage probabilities with parity-progression ratios and birth intervals for married women. These studies generated insights that might not have been apparent from a period perspective, such as changes in the incidence of childlessness or of very large families.

Studies based on a cohort perspective are not without problems, of course. First, cohort analyses require a great deal of birth and population data. Such data may be difficult to obtain for states and are often unavailable for counties and subcounty areas. Even when available, data for small areas may be unreliable due to small population sizes. When marriage rates, parity-progression ratios, and birth intervals are incorporated, cohort analyses become even more data-intensive. Period analyses require much less data.

Second, complete cohort fertility data become available only after women reach age 45 or 50. For younger women, only partial data can be used. In contrast, complete period data become available as soon as the relevant vital statistics and population data are tabulated.

Third, birth cohorts change over time because of deaths and migration. The members of the current cohort of women aged 45–49 living in a particular area may be quite different from those born there 45–49 years ago, especially for rapidly growing states and local areas. The foundation of cohort analysis thus changes over time.

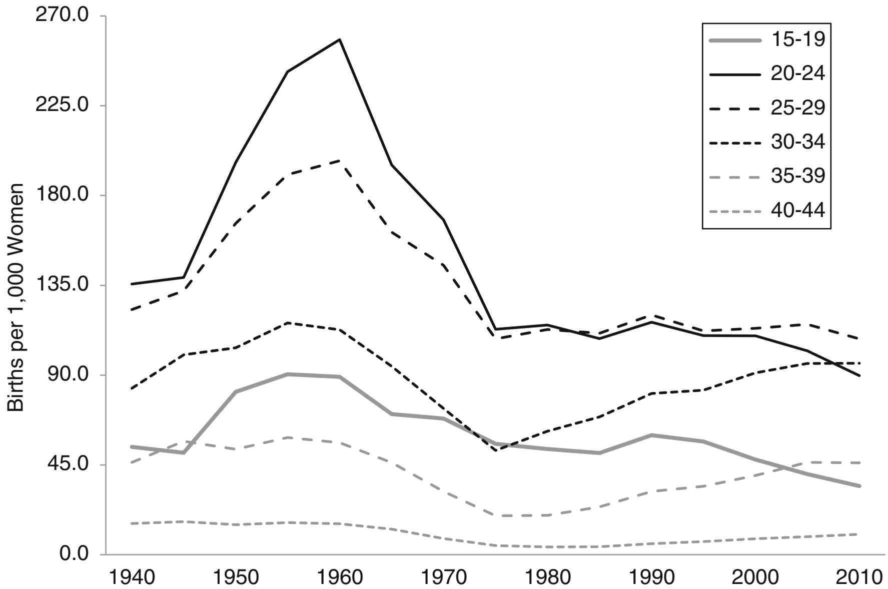

Fig. 5.2 Birth rates by age of mother, United States, 1940–2010 (Sources: Hamilton et al. (2011), U. S. Census Bureau (1961, 1985, 2012b))

Finally, the theoretical basis of the cohort perspective—that each birth cohort is unique and that this uniqueness persists over time—can be questioned. Some researchers not only believe there is little empirical evidence supporting this claim, but believe there is substantial evidence to the contrary (Ni Bhrolchain 1992). In particular, all cohorts appear to respond similarly to the factors affecting fertility behavior during any particular period of time. Figure 5.2 illustrates this point. ASBRs for all age groups between 15 and 39 in the United States rose substantially during the 1940s and 1950s and declined substantially during the 1960s and 1970s. A number of researchers have concluded that completed cohort fertility is not significantly different from an average of period fertility rates (Brass 1974; Ni Bhrolchain 1992; Foster 1990; Lee 1974).

Period analyses capture year-to-year changes in fertility behavior and use readily available data. Cohort analyses are consistent with the sequential nature of childbearing and reflect cumulative fertility levels. Each perspective illuminates particular aspects of fertility behavior, but for projection purposes we believe most practitioners will be better off using the period approach. Data for states and small areas are more readily available for period measures than for cohort measures. Perhaps more important, recent period data are available for all age groups, whereas complete cohort fertility data become available only after women have passed through their childbearing years. Furthermore, the theoretical basis of the cohort perspective—that each birth cohort is unique and that this uniqueness persists over time—is particularly questionable for states and local areas in which migration substantially alters the composition of a birth cohort over time.

The remainder of our discussion focuses on period fertility rates. However, the analyst should keep the cohort perspective in mind when formulating assumptions about fertility rates. Are changes occurring in the timing of births? If so, what impact will they have on completed family size? Does the current TFR provide a reasonable forecast of completed family size? Do current ASBRs provide a reasonable forecast of future ASBRs? If recent changes have occurred, do they reflect a shift in the long-run trend or were they simply short-run deviations from that trend? These questions can be answered only after considering both period and cohort perspectives.

5.3 Approaches to Projecting Fertility Rates

Although CBRs or GFRs are occasionally used for population projections, births in cohort-component models are typically projected by applying projected ASBRs to projections of the female population by age. In this section, we discuss the approaches most commonly used for projecting births and describe several specific models and techniques that can be used with each approach.

5.3.1 Constant Rates

One common approach to projecting fertility rates is to hold current ASBRs constant throughout the projection horizon (Day 1996; Treadway 1997; U. S. Census Bureau 2005). These rates are often based on the most recent year of data available, but can also be based on an average of several years. In many applications, they are calculated separately for different racial or ethnic groups. Holding rates constant can be justified on either of two grounds.

One is that future fertility rates are not likely to be much different from current rates. Although they fluctuated considerably over much of the twentieth century, TFRs in the United States have been fairly stable since 1990. Furthermore, TFRs and CFRs have been very similar over the last few decades; that is, period and cohort measures have given similar estimates of completed family size. Declining ASBRs for women younger than age 30 have been roughly offset by rising ASBRs for women above age 30. A reasonable argument can be made that fertility behavior in the United States has stabilized, making the continuation of current period rates a reasonable projection technique.

A second justification for holding birth rates constant is the belief that neither the direction nor the magnitude of future changes can be predicted accurately. The argument here is not that current rates *will* remain constant, but rather that scientific theories and historical data do not provide a reliable basis for predicting *how* those rates will change. If upward or downward movements are equally likely, current rates provide a reasonable forecast of future rates. This argument is supported by the generally lackluster forecasting performance of previous fertility projections.

For example, the vast majority of demographers failed to foresee either the timing or the magnitude of the baby boom and baby bust. This does not speak well for our ability to predict the course of future birth rates.

5.3.2 *Trend Extrapolation*

Another approach is based on the extrapolation of historical trends. This approach will be useful when birth rates have been changing in a systematic manner and are expected to continue to change systematically in the future. One early application of this approach calculated the rates of decline in ASBRs between 1925–1929 and 1930–1934 and extrapolated those rates into the future, with adjustments to allow for a gradual slowing in the rates of decline over time (Thompson and Whelpton 1933). Extrapolation techniques will be risky, of course, when no long-run trends are discernible or when there is no firm basis for forecasting turning points.

Time series modeling is a type of extrapolation that has become widespread over the last several decades, especially for projections at the national level. Some models have focused directly on births, ignoring age-specific rates, the age structure of the population, and even the total size of the population (McDonald 1981). However, it is more common to focus on ASBRs or summary fertility indexes, which are then converted into ASBR schedules (Alkema et al. 2011; Carter and Lee 1992; Lee and Tuljapurkar 1994). Time series models have been used for national fertility projections in the United States (U. S. Census Bureau 2008), Australia (Hyndman and Booth 2008), Europe (Alders et al. 2007), and elsewhere.

Time series models have two advantages over simple extrapolation techniques: They use more historical information and their point forecasts are accompanied by prediction intervals. However, forecasts from time series models are strongly affected by the structure of the models themselves and by the changes in births or birth rates occurring over the base period. These forecasts tend to move toward constant levels or converge toward constant oscillations within a fairly short time; they also tend to have very wide prediction intervals. Time series models would seem to be more useful for short-range forecasts (e.g., less than 5 years) than for long-range forecasts, especially for countries that have already gone through their demographic transitions from high to low fertility rates (Land 1986; Lee 1993).

5.3.3 *Targeting*

The targeting approach is based on the assumption that birth rates in the population to be projected will converge over time toward those found in another population (i.e., the target). The target rates can be those currently observed in the target population, rates projected for some future point in time, or rates based on the application of expert judgment. This approach is similar to the targeting approach for mortality rates described in Chap. 4.

The targeting approach can be implemented by forming ratios of current birth rates in the areas to be projected to current birth rates in the target population. Those ratios can then be projected to gradually move toward 1.0 over time. For example, one set of state projections produced by the Census Bureau assumed that ratios of state to national birth rates (by age and race) would move linearly to 1.0 by 2020 (U.S Census Bureau 1979). For each state, the projected ratios were applied to projected national birth rates to provide projections of state birth rates. A similar approach has been used to tie county birth rates to national rates (Nakosteen 1989).

The targeting approach can be applied to different racial/ethnic groups as well as to different geographic areas. For example, recent projections of the U.S. population produced by the Census Bureau held age-specific birth rates for non-Hispanic whites constant at levels observed between 1989 and 2009, while rates for other racial/ethnic groups were projected to gradually converge toward those rates over time (U.S. Census Bureau 2012a).

The assumption of convergence has some intuitive appeal, given the homogenizing influences of popular culture, mass communication, and inter-regional migration. The analysis of historical fertility trends provides ample empirical support for the convergence of birth rates among racial/ethnic groups in the United States, but provides only modest support for the convergence of birth rates among geographic areas: State and regional birth rates have converged during some time periods but not others (Ahlburg 1986; Isserman 1986). Recent projections made by the Census Bureau have *not* assumed that state birth rates would converge toward national birth rates over time (Campbell 1994, 1996; U. S. Census Bureau 2005) but—as noted above—have assumed convergence among racial/ethnic groups (U.S. Census Bureau 2012a). For any given set of projections, the analyst must make a judgment call regarding whether the convergence of age-specific birth rates among geographic areas or racial/ethnic groups is a reasonable assumption.

5.3.4 Synthetic Projection

Synthetic birth rates can be created by forming ratios of birth rates in one area to those in another and applying those ratios to the birth rates projected for the second area (called the *model population*). Although any two areas could be used, ratios are typically based on a smaller area and the larger area in which it is located (e.g., county/state or state/nation). ASBRs and GFRs are the measures most commonly used in constructing these ratios. For example, if (ASBR of County X)/(ASBR of State Y) = 1.1, the projected ASBR for County X would be obtained by multiplying the projected ASBR for State Y by 1.1.

Synthetic projection implicitly assumes that birth rates in the population to be projected will change at the same rate as birth rates in the model population; the analyst must decide whether or not this is a reasonable assumption. The synthetic approach is similar to targeting, but without assuming that birth rates in different areas will converge over time. This approach has been widely used for state and local projections (Campbell 1994, 1996; Wetrogan 1990).

5.3.5 Structural Models

Fertility is one of the most thoroughly studied topics in demography. Using the tools of economics, sociology, psychology, anthropology, biology, and other disciplines, researchers have tried to determine why fertility rates are higher for some individuals and populations than for others, and why those rates have changed over time. Many theories of fertility behavior have been developed, critiqued, challenged, and revised (Becker 1960; Easterlin 1987; Lesthaeghe 1983; Mason 1997; Schoen et al. 1997). Empirical investigations have considered the effects of income, education, religion, wages, female labor force participation, marriage, race/ethnicity, and other variables on fertility. The insights gained through these studies have been incorporated into several structural forecasting models (Ahlburg 1986; 1999; Sanderson 1999).

Using structural models for forecasting fertility rates has several problems (Isserman 1986; Land 1986). First, the determinants of fertility behavior are not completely understood, even after years of study. Consequently, the theoretical foundations of structural models are somewhat weak. Second, using a structural model requires the availability of forecasts of the model's independent variables. Such forecasts are often unavailable and, when they are, may not be very accurate. Third, forecasts from structural models are typically based on the assumption that the regression coefficients estimated from historical data will remain constant throughout the forecast horizon; this is not likely to be true. Finally, the data needed to construct structural models for small areas are seldom available.

We believe structural models of fertility are valuable for many analytical purposes, including simulation and policy analysis. However, we do not believe they are particularly useful for population forecasting at the state and local levels. We believe the resources needed to develop structural models for projecting fertility can be better used elsewhere. Chapter 9 provides a detailed discussion of structural forecasting models, but focuses on migration rather than fertility.

5.3.6 Expert Judgment

Many analysts base projections of fertility rates on their own judgment regarding future fertility trends. Expert judgment is typically informed by an evaluation of current fertility rates, historical trends, rates in other areas, and various economic, social, psychological, and cultural factors that might cause those rates to change. Although projections can be based *solely* on expert judgment by gathering data from a panel of experts and forming probabilistic projections (Lutz et al. 1999), expert judgment is more commonly used in combination with one or more of the techniques described above. For example, expert judgment has been used in conjunction with time series models to develop national fertility projections in the United States (U. S. Census Bureau 2008) and Europe (Alders et al. 2007).

5.4 Implementing the Fertility Component

5.4.1 Sources of Data

Whenever possible, fertility projections should take into account the age and sex structure of the population. To construct ASBRs and TFRs, the analyst must have data on the number of births by age of mother (for the numerator) and counts or estimates of the population by age and sex (for the denominator). Annual birth data are available for states and counties with more than 100,000 residents from the NCHS; data for counties with fewer than 100,000 residents are typically available from each state's office of vital statistics. Because of fluctuations in fertility behavior over time (especially for small counties), it is common to use a 3-year average of births (e.g., 2009–2011) instead of births from a single year in constructing ASBRs. Birth data by race and ethnicity are generally available for large counties but not always for small counties.

Population counts by age, sex, race, and Hispanic origin for states, counties, and subcounty areas are available every 10 years from the decennial census. For non-census years, population estimates must be used. The Census Bureau produces annual estimates by age, sex, race, and Hispanic origin for states and counties. In addition, county-level estimates of population characteristics can often be obtained from state demographic agencies or other sources (e.g., private data companies). Because population estimates are less accurate than decennial census data, ASBRs based on intercensal or postcensal estimates are less reliable than those based on decennial census data.

The birth data needed for constructing ASBRs are not available for most subcounty areas. In addition, subcounty population estimates by age, sex, race, and Hispanic origin are seldom available for non-census years. Consequently, ASBRs for cities, census tracts, traffic analysis zones, and other subcounty areas are rarely available.

What can the analyst do when ASBRs are not available at the subcounty level? The most common solution is simply to use county- or state-level ASBRs. This approach will often provide reasonable proxies for small-area ASBRs. However, in some circumstances it may be important to account for differences in racial/ethnic composition between the small area and the county (or state) because birth rates often differ by race and ethnicity. This can be done in several ways. One is to make separate projections for each racial/ethnic group, using the appropriate ASBRs for each group. Another is to calculate a weighted average of the ASBRs for racial/ethnic groups, with the weights determined by the proportion of the area's female population found in each racial/ethnic group, by age. For example, if whites account for 75% of the female population of an age group and blacks for 25%, that ASBR could be calculated as:

$$\text{ASBR} = 0.75\ (\text{white ASBR}) + 0.25\ (\text{black ASBR})$$

5.4.2 Views of the Future

As was true for mortality projections, the methods and assumptions chosen for projecting fertility rates will be affected by the analyst's views of the future. However, uncertainty regarding future change is greater for fertility rates than for mortality rates. Mortality rates have been steadily falling for many decades and most observers believe they will continue falling; the main question is how far and how rapidly they will fall. Fertility rates, on the other hand, have experienced large declines *and* large increases during the last 100 years. Which way will future rates move? Will they change a lot or only a little? The analyst's answers to these questions will have a large impact on the choice of techniques and assumptions used in projecting fertility rates.

The starting point, then, must be the development of an informed outlook regarding future fertility trends. Demographic transition theories have offered explanations for why fertility rates in more developed countries moved from high to low levels over the last two centuries, focusing on factors such as the rising costs and declining economic benefits of children, declines in infant and child mortality, and changes in female roles in the household and society (Caldwell 1982; Guinnane 2011; Lee 2003; Mason 1997). Economists, sociologists, anthropologists, psychologists, and others have offered explanations for why people continue to have children in post-transition societies (Becker 1960; Margolis and Myrskyla 2011; Morgan 2003; Schoen et al. 1997). This question was framed most starkly (and sardonically) by economist Joseph Schumpeter: "Why should we stunt our ambitions and impoverish our lives in order to be insulted and looked down upon in our old age?" (quoted in Weeks 2012, p. 216).

Why indeed? What social, psychological, cultural, economic, and religious factors cause people to continue having children in the twenty-first century? The answer to this question lies at the heart of any discussion of future fertility rates. Will American fertility rates decline to the very low levels found in a number of European and Asian countries? Will there be another baby boom? Or, have fertility rates in the United States reached some sort of equilibrium level at which they will remain for a long time to come? The analyst must answer these questions before choosing techniques and assumptions for projecting fertility rates.

Additional factors must be considered when making projections for states and local areas. Income, education, and occupation—as well as race and ethnicity—vary considerably from one place to another. These characteristics often have significant effects on fertility rates. The presence of a college, prison, military base, or other institution may also have a substantial impact on aggregate fertility measures. Differences in fertility rates are much greater among subcounty areas than they are among states or even counties (Bogue 1998). Realistic projections will be possible only if these differences are accounted for in the projection process.

We suggest that the analyst thoroughly review the underlying data before developing fertility assumptions. Period birth rates by age of mother should be examined to determine whether any unusual patterns are present and, if so, what caused them. Trends in TFRs and individual ASBRs must be considered. If recent changes in period rates have occurred, some assessment must be made as to whether they reflect a shift in the long-run trend or simply a short-run deviation from that trend. It is essential to view fertility rates from both a period and a cohort perspective, evaluating changes in the timing of births and the potential impact of those changes on completed family size.

If large institutional populations are present, their impact on ASBRs must be accounted for. Changes in racial, ethnic, and socioeconomic characteristics must be considered and decisions made regarding their impact on future fertility rates (e.g., whether rates for various racial or ethnic groups will converge over time). Especially for small areas, the quality of the underlying fertility and population data must be evaluated and adjustments made if anomalies or errors are found. Even the most prescient set of assumptions will be useless if there are errors in the underlying data.

5.4.3 Examples

The following examples illustrate several ways to project fertility rates. The first is a set of national projections produced by the Census Bureau in the mid-1970s (U.S. Census Bureau 1975). These projections were based on a cohort fertility model, using historical fertility data and birth expectations data from 1971 to 1974. Three fertility assumptions were made. The medium assumption projected an ultimate cohort fertility rate of 2.1, while the low and high assumptions projected ultimate rates of 1.7 and 2.7, respectively. Cohort fertility rates for whites and blacks were projected to converge over time, with the ultimate rates first being achieved by the 1965 birth cohort for whites and by the 1970 birth cohort for blacks. Period ASBRs for the years prior to reaching the ultimate rates were calculated by interpolating between the values for 1973 (the last year for which estimates were available) and their ultimate values. They were adjusted so that observed and projected rates would be consistent with completed cohort fertility rates. Projected ASBRs and TFRs for 1975, 1995, and 2015 are shown in Table 5.4.

It is interesting to compare these projections with a set produced in the mid-1990s (Day 1996). The more recent projections were based on a period fertility approach rather than a cohort approach. The reason for this change was the observation that completed cohort fertility had remained fairly stable for several years, making current

Table 5.4 Projected age-specific birth rates and total fertility rates, United States, 1975–2015

Assumption-year	10–14	15–19	20–24	25–29	30–34	35–39	40–44	45–49	TFR[a]
Low-1975	1.0	54.3	110.0	99.5	49.1	20.0	5.0	0.4	1.70
Low-1995	0.2	38.8	116.5	114.4	50.4	16.6	4.0	0.3	1.71
Low-2015	0.2	37.3	116.8	117.8	50.1	14.2	3.3	0.2	1.70
Medium-1975	1.1	58.5	120.1	107.4	51.4	20.6	5.2	0.3	1.82
Medium-1995	0.3	47.5	143.8	142.0	63.0	20.7	4.9	0.3	2.11
Medium-2015	0.3	46.1	144.4	145.5	61.9	17.6	4.0	0.3	2.10
High-1975	1.1	65.4	131.1	117.0	54.7	21.7	5.4	0.4	1.98
High-1995	0.4	60.4	184.3	183.0	81.6	26.7	6.1	0.4	2.71
High-2015	0.4	59.2	185.6	187.1	79.6	22.6	5.2	0.4	2.70

Source: U.S. Census Bureau (1975)

[a]5 × (Sum of the age-specific rates) / 1,000

period rates a reasonable proxy for cohort rates (Day 1996). The starting point for these projections was a set of ASBRs calculated for five race-ethnicity groups: Hispanic, non-Hispanic white, non-Hispanic black, non-Hispanic American Indian, and non-Hispanic Asian. These rates were based on fertility data from 1990 to 1992 and population data for July 1, 1991. The population data were adjusted for net census coverage error using demographic analysis.

These projections used three fertility assumptions. Under the medium assumption, ASBRs were projected to remain constant for each racial/ethnic group; that is, they were *not* projected to converge over time. Because the five race-ethnicity groups were growing at different rates, however, the medium assumption produced overall ASBRs and TFRs that increased gradually over time (see Table 5.5). Under the high fertility assumption, ASBRs for each race-ethnic group were projected to rise by 15% by 2010. In the low series, they were projected to decline by 15%.

A comparison of Tables 5.4 and 5.5 shows the TFRs for the medium projections to be quite similar: 2.11 (1995) and 2.10 (2015) in Table 5.4 and 2.06 (1995) and 2.14 (2020) in Table 5.5. The age patterns of childbearing are considerably different, however. ASBRs for women 30–39 are consistently higher in Table 5.5 than Table 5.4 and ASBRs for women 20–29 are consistently lower. These differences reflect the trend toward delayed childbearing occurring over the last several decades.

The Census Bureau also produced a set of state projections consistent with each of these sets of national projections. The first set started with ASBRs by race for each state, based on data from 1970 to 1975 (U.S Census Bureau 1979). Ratios of state/national rates were constructed and were projected to move linearly toward 1.0, reaching that level by 2020. In other words, it was assumed that state ASBRs would converge toward national ASBRs over time. As a final step, state ASBRs were calculated by multiplying the interpolated ratios by the medium set of national ASBRs.

The second set of state projections started with ASBRs calculated for five racial-ethnic groups for each state (Campbell 1996). These rates were based on the annual average number of births in each state between 1989 and 1993. Rates were held

Table 5.5 Projected age-specific birth rates and total fertility rates, United States, 1995–2050

Assumption-year	10–14	15–19	20–24	25–29	30–34	35–39	40–44	45–49	TFR[a]
Low-1995	1.4	59.4	115.4	117.8	78.9	31.6	5.6	0.3	2.06
Low-2020	1.4	55.5	103.0	102.8	69.1	28.2	5.3	0.3	1.82
Low-2050	1.6	59.3	108.9	105.7	70.9	29.8	5.7	0.3	1.91
Medium-1995	1.4	59.4	115.4	117.8	78.9	31.6	5.6	0.3	2.06
Medium-2020	1.6	64.8	121.0	120.9	81.3	33.2	6.2	0.3	2.14
Medium-2050	1.8	69.7	128.2	124.2	83.8	34.9	6.8	0.4	2.24
High-1995	1.4	59.4	115.4	117.8	78.9	31.6	5.6	0.3	2.06
High-2020	1.9	74.1	139.1	139.0	93.5	38.2	7.2	0.3	2.47
High-2050	2.1	80.0	147.5	142.7	95.6	40.1	7.8	0.4	2.58

Source: Day (1996)

[a]5 × (Sum of the age-specific rates) / 1,000

constant throughout the projection horizon; that is, it was *not* assumed that state rates would converge toward national rates over time.

The most recent set of state projections followed a simple procedure by holding current ASBRs constant for each state (U. S. Census Bureau 2005). The Census Bureau has not produced any state projections since that time, but is tentatively planning to produce a new set by 2015.

In these examples—and in most other applications of the cohort-component method—births are projected by multiplying projected ASBRs by the projected female population. Chapter 7 provides several illustrations of how this process can be carried out. A final example will be given here to show how births (or, more precisely, the population in the youngest age group) can be projected indirectly *without* the use of ASBRs.

Suppose that projections are to be made for census tracts, but there are no birth data at the tract level. What can be done? One option is to develop a set of tract-specific ASBRs using indirect techniques, as suggested by Bogue (1998). Developing these rates, however, would require a great deal of time and effort, making this an expensive option. Another option is to use county-level ASBRs for each census tract. This will be a viable option in many circumstances, but may not provide reasonable results if there is a great deal of socioeconomic and demographic diversity among census tracts.

A third option is to construct a set of child-woman ratios and apply those ratios to the projected female population aged 15–44. These ratios can be based on tract-specific data from the most recent census. To take a hypothetical example, suppose that a tract's 2010 population included 400 children aged 0–4 and 1,100 women aged 15–44, yielding a child-woman ratio of 0.3636. Suppose that the projected female population aged 15–44 in 2015 is 1,200. The population aged 0–4 in 2015 could be projected as:

$$0.3636\ (1{,}200) = 436$$

An alternative approach is to assume that the child-woman ratio in the census tract will change at the same rate as the child-woman ratio in a larger area, such as the county, or converge toward a target level over time. For example, if the child-woman ratio for the county was 0.35 in 2010 and was projected to decline to 0.33 by 2015, the population aged 0–4 in 2015 could be projected as:

$$0.3636\ (1{,}200)\ (0.33/0.35) = 411$$

This adjustment allows the analyst to account for projected changes in fertility rates and age structure, while still incorporating the impact of tract-level fertility characteristics. This approach offers a compromise between spending a large amount of resources developing tract-specific fertility rates and completely ignoring the existence of tract-level differences in fertility rates.

5.5 Conclusions

It has often been noted that fertility is the most problematic part of national population projections (Keyfitz 1982; Ryder 1990; Siegel 1972). For example, Long (1989) found that differences in fertility assumptions accounted for more of the variation in long-run projections of the U.S. population than did differences in either mortality or immigration assumptions. Clearly, fertility assumptions are critical to the preparation of national population projections.

For states and local areas, however, fertility is usually less important than migration in explaining differences in rates of population growth (Congdon 1992; Smith and Ahmed 1990). At the subnational level, migration rates vary more from place to place and change more dramatically over time than do fertility rates. Fertility rates, however, display more variation than do mortality rates. As a result, fertility rates can generally be forecasted more accurately than migration rates, but not as accurately as mortality rates. Fertility assumptions typically have more impact on state and local population projections than do mortality assumptions, but not as much as migration assumptions.

Whereas differences in mortality assumptions have their largest impact at older ages, differences in fertility assumptions have their largest impact at younger ages. Changes in mortality and migration rates affect all age groups, but changes in fertility rates immediately affect only the youngest. Long (1989) found fertility to be the major cause of variability in national projections of the youngest age groups. In a study of county population projections, Isserman (1993) found differences in fertility assumptions to have a much larger impact on the youngest age group than on the population as a whole. Over time, of course, the effects of differences in fertility rates are cumulative and fertility assumptions have a major impact on both the size and the age structure of the population (Siegel 2002, p. 596).

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Chapter 6
Migration

The United States is a nation of movers. In a typical year, about 15% of the U.S. population moves to a different place of residence. Table 6.1 provides an overview of moving in the United States between 2009 and 2010. Of the 305.6 million residents aged 1 and older in 2010, 258.6 million were living in the same house as in 2009, 45.3 million had moved from another house in the United States, and 1.8 million had moved from abroad. Of movers within the United States, about 64% moved to a different house in the same county, 21% moved to a different county in the same state, and 15% moved to a different state.

Given this propensity for moving, it is not surprising that the United States is among the countries with the highest migration rates (Molloy et al. 2011). About 5.4% of the U.S. population moved from one county to another between 2009 and 2010. Contrast this with Estonia, for example, where only 1.3% of the population moved from one county to another in that year (Statistics Estonia 2010). About 0.6% of the U.S. population in 2010 moved from abroad during the previous year, compared to about 0.2% of the population in Estonia.

The United States shares high mobility and migration rates with a number of other countries in which the official language (or one of them) is English, including Australia, Canada, and New Zealand. These four countries share longstanding traditions of immigration, cultural values that emphasize personal freedom, and public policies and housing markets that facilitate mobility (Gober 1993; Molloy et al. 2011). At current rates, Americans will average 11–12 changes in residence during their lifetimes (U.S. Census Bureau 2012a).

Moving rates vary considerably from state to state. For the nation as a whole, 2.2% of the population aged 1 and over lived in a different state in 2010 than in 2009. In the District of Columbia, 8.5% of the population aged 1 and over in 2010 lived in a different state than in 2009, compared to only 1.2% in California (U.S. Census Bureau 2012b). Differences are even greater at the county level. During the period from 2005 to 2009, 23.5% of the population aged 1 and older living in the Aleutians West Census Area (a "county equivalent") moved from a different state, whereas no person aged 1 and older in Taylor County, Georgia moved from a different state during that period (U.S. Census Bureau 2012c).

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Table 6.1 Movers in the United States, 2009–2010

Residence 1 year ago	Number	Percent
Population 1 year and older	305,628,607	(X)
Same house	258,552,348	84.6
Different house in the U.S.	45,326,114	14.8
Same county	28,850,018	9.4
Different county	16,476,096	5.4
Same state	9,732,867	3.2
Different state	6,743,229	2.2
Abroad	1,750,145	0.6

Source: Table DP02, Selected Social Characteristics in the United States 2010 American Community Survey 1-Year Estimates

Combined with the potential for rapid changes in moving rates, these huge differences make it difficult to forecast migration accurately. In this chapter, we discuss a variety of concepts, measures, and definitions of mobility and migration (see Box 6.1 for a summary of commonly used terms). We discuss a number of data sources and describe several methods for measuring migration. To set the stage for developing assumptions regarding future migration patterns, we consider the determinants of migration and some of the characteristics of migrants. We then describe the data and techniques that can be used to project future migration flows, focusing on issues with particular importance for states and local areas. We close with an assessment of the impact of migration on population projections.

Box 6.1 Some Common Migration Definitions

Mover: A person who changes his/her place of usual residence from one address (e.g., house or apartment) to another.

Migrant: A person who changes his/her place of usual residence from one political or administrative area to another.

Immigrant: A citizen or permanent resident of one country who has been legally admitted to the host country in order to establish permanent residence there.

Emigrant: A citizen or permanent resident of the host country who moves to a different country in order to establish permanent residence there.

Gross Migration: The movement of migrants into or out of an area.

Net Migration: The difference between the number of in-migrants and the number of out-migrants.

Internal (Domestic) Migration: Migration from one place to another within the same country.

International (Foreign) Migration: Migration from one country to another.

Migration Interval: The period of time over which migration is measured.

6.1 Concepts, Definitions, and Measures

It is much more difficult to measure or even to define migration than either mortality or fertility. This is especially true for countries lacking a full population registration system, such as the United States, which registers births and deaths but not migration. Unlike births and deaths, migration involves two areas, one of origin and one of destination. Some moves cover short distances, others cover long distances. Some moves are temporary, others are permanent. Furthermore, people are born and die only once but can move many times. How can mobility and migration be defined and measured?

6.1.1 Place of Residence

For many Americans, the simple question "Where do you live?" does not have an equally simple answer. Many retirees spend summers in New York, Illinois, or Minnesota and winters in Arizona, Florida, or Texas. Itinerant farm workers follow the harvest from place to place over the course of a year. Dual-career couples may have one spouse working in New York City and the other working in Washington, DC, getting together only on weekends. Children of divorced couples may spend alternating weeks or months with each parent. Some college students spend the school year in Madison, Wisconsin or Ithaca, New York and the summer in Milwaukee or Buffalo. Members of rock bands and professional basketball teams spend much of the year moving from city to city. A soldier serving in Afghanistan may have Fort Campbell, Kentucky as his or her "home of record." We know a professor at the University of California, Riverside who is a registered voter and owns a home in Las Vegas, endures a weekly commute between Las Vegas and Riverside when classes are in session, stays in a small rental flat in Riverside during the week, and files a non-resident state income tax return in California. Where do these people live?

The answer to this question is crucial because mobility and migration typically refer to "changes in one's place of usual residence." In the United States, "usual residence" is defined as the place a person lives and sleeps more than any other place (Cork and Voss 2006, p. 2). Under this definition, people with two or more homes are counted at the one in which they spend the most time, college students are counted at the place they are staying while attending college, and members of the armed forces are counted at the location where they are based. If a person has no usual place of residence, he or she is counted at the place he or she was staying on census (or estimation day).

Due to this focus on changes in usual (or "permanent") residence, traditional measures of mobility and migration miss temporary moves such as commuting to work, shifting between weekday and weekend homes, seasonal migration, business trips, vacations, and life on the road in a recreational vehicle. These non-permanent moves are large in number and can have a substantial impact on both the sending and receiving regions (Behr and Gober 1982; Happel and Hogan 2002; McHugh et al. 1995; Rogers et al. 2010; Smith 1989; Swanson and Tayman 2011). Unfortunately, the data needed to measure and evaluate temporary moves are sorely lacking and temporary population movements have received relatively little attention among researchers in the United States and most other countries.

Population projections typically refer to the permanent resident population of a state, county, or subcounty area. Accordingly, the measures of mobility and migration discussed in this chapter focus solely on changes in one's place of usual residence. Temporary, cyclical, and season migration are important research topics, but lie outside the scope of this book.

6.1.1.1 Mobility and Migration

Although *mobility* can refer to changes in social or occupational status, to a demographer it generally means changes in geographic location. We define mobility as any change in one's place of usual residence from one address (e.g., house or apartment) to another. The destination of a move can be as close as the apartment building across the street or as far as a house across the country or around the world.

Migration, on the other hand, refers to moves across some type of political, administrative, or statistically-defined boundary (Swanson and Stephan 2004). This distinction is intended to differentiate between moves within a community and moves from one community to another (or, more broadly, to differentiate between short- and long-distance moves). This distinction is critical for some types of analyses, but not for the topics addressed in this book. Our focus is on population projections for states, counties, and subcounty areas such as cities, census tracts, school districts, and market areas. We define all moves into or out of these geographic areas as migration, regardless of the distance moved, the degree of change in the living environment, or the size of the geographic area. Given this focus, there is no need to differentiate between migration and mobility.

6.1.1.2 Gross and Net Migration

Migration can be viewed from either of two perspectives. *Gross migration* is the movement of people into or out of an area; *net migration* is the difference between the two. Table 6.2 shows in-, out-, and net migration for every state and the District of Columbia between 2009 and 2010. These numbers exclude people coming from abroad, Puerto Rico, and outlying territories such as American Samoa. As such, they represent "domestic migration."

Texas had 486,558 in-migrants and California had 573,988 out-migrants; these represent the largest numbers of any state. Texas also had the largest net in-migration balance (74,917) and California had the largest net out-migration balance (−129,239). The state with the smallest number of in-migrants was

Table 6.2 In-migrants, out-migrants and net migrants, by state, 2009–2010[a]

	In-migrants	Out-migrants	Net migration
Northeast			
Connecticut	77,333	89,360	−12,027
Maine	27,758	32,209	−4,451
Massachusetts	140,162	144,152	−3,990
New Hampshire	39,367	38,399	968
New Jersey	127,369	193,972	−66,603
New York	269,427	363,139	−93,712
Pennsylvania	235,580	209,810	25,770
Rhode Island	32,059	24,948	7,111
Vermont	22,529	18,380	4,149
Midwest			
Illinois	203,959	277,579	−73,620
Indiana	127,353	130,170	−2,817
Iowa	72,557	66,922	5,635
Kansas	95,059	90,681	4,378
Michigan	116,149	178,207	−62,058
Minnesota	89,872	104,765	−14,893
Missouri	145,226	148,055	−2,829
Nebraska	51,290	43,531	7,759
North Dakota	30,100	24,450	5,650
Ohio	172,633	188,013	−15,380
South Dakota	25,777	27,915	−2,138
Wisconsin	93,065	111,240	−18,175
South			
Alabama	108,723	99,221	9,502
Arkansas	79,127	64,264	14,863
Delaware	30,759	30,055	704
District of Columbia	51,244	56,052	−4,808
Florida	482,889	427,853	55,036
Georgia	249,459	244,992	4,467
Kentucky	118,443	92,999	25,444
Louisiana	97,889	88,131	9,758
Maryland	164,484	159,866	4,618
Mississippi	72,321	68,363	3,958
North Carolina	263,256	207,025	56,231
Oklahoma	106,511	90,616	15,895
South Carolina	152,441	117,569	34,872
Tennessee	159,778	143,135	16,643
Texas	486,558	411,641	74,917
Virginia	259,507	232,002	27,505
West Virginia	39,609	49,349	−9,740

(continued)

Table 6.2 (continued)

	In-migrants	Out-migrants	Net migration
West			
Alaska	36,326	94,692	−58,366
Arizona	222,725	176,768	45,957
California	444,749	573,988	−129,239
Colorado	186,366	140,620	45,746
Hawaii	53,581	49,218	4,363
Idaho	55,638	53,122	2,516
Montana	35,630	35,870	−240
Nevada	102,677	109,409	−6,732
New Mexico	73,605	50,438	23,167
Oregon	116,700	100,185	16,515
Utah	77,780	75,541	2,239
Washington	191,784	166,162	25,622
Wyoming	28,046	28,186	−140

Source: U.S. Census Bureau 2012b
[a]Domestic migrants only, excluding international migration

Vermont (22,529); it also had the smallest number of out-migrants (18,830). Delaware had the smallest net in-migration balance (704) and Wyoming had the smallest net out-migration balance (−140).

Data can also be tabulated for specific place-to-place migration flows. For example, of the 486,558 people moving to Texas between 2009 and 2010, 28,238 had been living in Oklahoma in 2009 (U.S. Census Bureau 2012b). Conversely, of the 106,511 people moving to Oklahoma between 2009 and 2010, 26,969 came from Texas. Thus, the net flow between Texas and Oklahoma was 1,269 (28,238–26,969), with Texas the net gainer and Oklahoma the net loser. Specific state-to-state (and county-to-county) migration flows can be useful for analyzing the determinants and consequences of migration and for developing multi-regional projection models (Rogers 1985, 1995).

There are several advantages in using gross rather than net migration data for population projections (Rogers 1990; Smith and Swanson 1998). First, gross migration is closer to the true migration process than is net migration. Some people move into an area, some move out, and others stay put. People may therefore be classified as movers or non-movers and as in-migrants or out-migrants, but there is no such thing as a "net migrant." Net migration is an accounting procedure, not a migration process.

Second, focusing on net migration may mask the existence of large gross migration flows. Delaware had a domestic net migration balance of only 704 between 2009 and 2010 (Table 6.2). Does this mean that only a few people were moving into or out of Delaware? Absolutely not. The state had 30,759 in-migrants and 30,055 out-migrants between 2009 and 2010. Gross migration data illuminate those moves, net migration data obscure them.

Third, gross migration data can be related to the size of the source population from which migrants come, providing migration rates that approximate the probability of migrating. Because net migration data simply represent the difference between the numbers of in- and out-migrants, they have no identifiable source populations. Consequently, net migration rates do not reflect migration probabilities.

Fourth, when net migration is calculated from the demographic balancing equation as the difference between total population change and natural increase, it captures all the measurement errors found in birth, death, and total population data. These errors may be substantial (Isserman et al. 1982).

Finally, population projections based on net migration models sometimes lead to unrealistic forecasts. When in- and out-migration flows are projected separately, the projection model can account for differences in the demographic structures and rates of growth of both the origin and destination populations. When in- and out-migration flows are combined to form net migration, however, the model cannot account for these differences. As demonstrated by Isserman (1993), Plane (1993), and Smith (1986), projections based on net migration models can differ considerably from projections based on gross migration models, particularly for areas that are growing rapidly. We suggest ways for reducing these differences later in this chapter.

Although gross migration models have a number of advantages for the production of cohort-component population projections, net migration models have several advantages as well (Smith and Swanson 1998). They require less data and are simpler to apply than gross migration models, making them considerably less resource intensive. Perhaps more important, they can be used when the data required by gross migration models are unreliable or simply do not exist; this is particularly important when making projections for small areas. Finally, if appropriate precautions are taken, there is nothing inherent in net migration models causing them to produce less accurate forecasts than gross migration models, especially for short- and medium-range projection horizons. We believe there are many circumstances in which net migration models are more useful than gross migration models. We give examples of both types of model in Chap. 7.

6.1.1.3 Length of Migration Interval

Migration data are typically derived from censuses, surveys, or administrative records which report a person's current place of residence and his or her place of residence at some earlier point in time. For our purposes, a migrant is defined as a person whose current place of residence is located in a different geographic area than his/her earlier place of residence. National statistical offices have traditionally used either 1- or 5-year intervals for developing gross migration statistics (Long and Boertlein 1990). When net migration data are derived from two consecutive decennial censuses using the demographic balancing equation, the interval is 10 years. What length of interval is best?

There is no definitive answer to this question. Migration data covering different intervals simply reflect different aspects of the migration process. Short intervals pick up most moves but are heavily affected by chronic movers and moves that turn out to be temporary (Ihrke and Faber 2012; Morrison and DaVanzo 1986). Long intervals cancel out some of the effects of chronic and temporary movers; consequently, they may provide a better measure of long-term mobility. However, they miss the impact of multiple moves within the time interval and introduce measurement errors for people who are unable to recall accurately the timing or location of earlier moves. Long intervals also miss more people who move but die than do short intervals. For any particular application, then, the appropriate length of interval will depend on the availability of data and the purposes for which the data will be used.

In the United States, migration data were collected in the long form of every decennial census between 1940 and 2000 (the long form was a more detailed questionnaire sent to a sample of households). These data referred to a 5-year period in every year except 1950, when 1-year migration data were collected because of the disruptive effects of World War II. However, migration data are no longer collected in the decennial census because the census no longer includes a long form. Migration data are now collected in the American Community Survey (ACS), which focuses on migration over a 1-year rather than a 5-year period (U.S. Census Bureau 2009b). This change has important implications for the construction of population projections.

Because of the impact of multiple moves and deaths of migrants, migration data for one length of interval are not directly comparable to migration data for another length of interval. Whereas birth and death data can be converted easily into intervals of different lengths, attempting to convert migration data is a complex and somewhat capricious undertaking. We return to this issue later in this chapter.

6.1.1.4 Migration Rates

A fundamental methodological problem in constructing cohort-component projections is choosing the appropriate population base (i.e., the denominator) for calculating mortality, fertility, and migration rates. Theoretically, the appropriate base for any rate is the population exposed to the risk of the occurrence of the event under consideration. For mortality and fertility, the choice is clear: For purposes of projection, the population exposed to the risk of dying or giving birth is the population of the state or local area being projected (adjusted to reflect the total number of person-years lived during the time period). For migration rates, however, the choice is not so clear. What is the population exposed to the risk of migrating?

A number of studies have addressed this question. Most, however, focused primarily on whether the initial, terminal, or mid-point population should be used to calculate migration rates, and what adjustments for births, deaths, and migration during the time period should be made to estimate the total number of person-years lived (Edmonston and Michalowski 2004; Hamilton 1965; Morrison et al. 2004). These are important issues, but they do not address critical questions regarding exposure to the risk of migration.

In fact, many studies have simply used the population of the area under consideration as the denominator in the construction of migration rates, regardless of whether those rates referred to in-migration, out-migration, or net migration (Long 1988; Meuser and White 1989). Yet the population of the area itself is clearly not the population exposed to the risk of in-migration; after all, those people already live in the area. For net migration the issue is even more difficult because net migration is a residual rather than an actual event; consequently, it has *no* true at-risk population. Only for out-migration does the area under consideration represent the population exposed to risk; therefore, only for out-migration can rates be calculated that approximate the probability of migrating. For in-migration and net migration, "rates" calculated in this manner are simply migration/population ratios. They provide measures of the contributions of in-migration or net migration to population size, but provide no information on the propensity to migrate.

In-migration rates that approximate the probability of migrating can be developed, however, by basing rates on the population of the area of origin rather than the area of destination. For example, we can construct domestic gross migration rates for Arizona by using the population of Arizona as the denominator for out-migration rates and the population of the rest of the United States (that is, the national population minus the Arizona population) as the denominator for in-migration rates; we call the latter the "adjusted" U.S. population. In-migration rates can also be defined for specific states or regions through the use of multi-regional models, but this requires much more detailed data than is needed for a simple two-region model.

The migration data used in this example came from Public Use Microdata Sample (PUMS) files for 2010; these files are based on a sample of ACS respondents. Domestic in-migrants were tabulated using the file for the state of Arizona and were defined as all respondents living in Arizona in 2010 who reported they lived in some other state in 2009. Domestic out-migrants were tabulated using the file for the United States and were defined as all respondents living in other states in 2010 who reported they lived in Arizona in 2009. Table 6.3 shows the number of males and females entering and leaving Arizona between 2009 and 2010 for selected single years of age, along with the population data needed to construct migration rates. Because they are based on place of residence 1 year ago, ACS migration data are best suited for cohort-component models with single-year age groups and 1-year projection intervals.

Migration rates for each age-sex group are calculated by dividing migration by the appropriate population in 2009, which represents the beginning of the migration period. To calculate in-migration rates, we divide the number of in-migrants by the adjusted U.S. population. For example, there were 4,508 male in-migrants aged 23 in 2009 and 2,073,186 males aged 23 who lived outside Arizona in 2009, yielding an in-migration rate of:

$$4{,}508/2{,}073{,}816 = 0.00217$$

or 2.17 in-migrants per 1,000 persons. To calculate out-migration rates, we divide the number of out-migrants by the Arizona population. There were 3,290 male out-migrants aged 23 and 43,956 males aged 23 living in Arizona in 2009, yielding an out-migration rate of:

$$3{,}290/43{,}956 = 0.07485$$

Table 6.3 Domestic migration rates by selected single year of age and sex, Arizona, 2009–2010

Males								
				Jan 1, 2009 population				
2009 age	2010 age	In-migr	Out-migr	U.S.	Arizona	Adjusted U.S[a]	In-migration rate[b]	Out-migration rate[c]
1	2	1,013	751	2,009,008	45,364	1,963,644	0.52	16.55
2	3	1,831	1,369	2,069,693	46,808	2,022,885	0.91	29.25
3	4	1,451	1,223	2,081,913	47,352	2,034,561	0.71	25.83
4	5	2,433	1,702	2,055,203	46,174	2,009,029	1.21	36.86
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
20	21	3,365	3,042	2,283,490	48,146	2,235,344	1.51	63.18
21	22	2,121	2,395	2,199,284	45,852	2,153,432	0.98	52.23
22	23	3,238	2,384	2,154,372	44,671	2,109,701	1.53	53.37
23	24	4,508	3,290	2,117,772	43,956	2,073,816	2.17	74.85
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
45	46	612	434	2,213,383	42,316	2,171,067	0.28	10.26
46	47	437	1,286	2,206,985	41,634	2,165,351	0.20	30.89
47	48	1,067	661	2,214,172	42,140	2,172,032	0.49	15.69
48	49	892	825	2,213,664	42,025	2,171,639	0.41	19.63
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
60	61	1,092	470	1,726,732	34,219	1,692,513	0.65	13.74
61	62	1,637	676	1,661,016	33,372	1,627,644	1.01	20.26
62	63	1,096	427	1,694,270	35,320	1,658,950	0.66	12.09
63	64	1,702	794	1,654,341	35,021	1,619,320	1.05	22.67
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
81	82	273	232	489,547	11,162	478,385	0.57	20.78
82	83	183	103	458,003	10,082	447,921	0.41	10.22
83	84	128	50	415,315	8,981	406,334	0.32	5.57
84+	85+	1,212	840	2,139,545	45,320	2,094,225	0.58	18.53
State Total		116,596	88,327	148,156,094	3,094,312	145,061,782	0.80	28.54

Females								
				Jan 1, 2009 population				
2009 age	2010 age	In-migr	Out-migr	U.S.	Arizona	Adjusted U.S[a]	In-migration rate[b]	Out-migration rate[c]
1	2	2,018	1,319	1,926,374	43,258	1,883,116	1.07	30.49
2	3	799	1,609	1,983,272	45,239	1,938,033	0.41	35.57
3	4	1,117	1,181	1,992,927	45,351	1,947,576	0.57	26.04
4	5	1,014	1,347	1,964,366	43,998	1,920,368	0.53	30.62
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
20	21	2,771	3,315	2,187,145	44,437	2,142,708	1.29	74.60
21	22	1,901	2,165	2,108,284	42,372	2,065,912	0.92	51.10
22	23	2,526	2,856	2,064,507	40,750	2,023,757	1.25	70.09
23	24	2,656	1,382	2,035,745	40,731	1,995,014	1.33	33.93
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
45	46	444	477	2,247,104	42,009	2,205,095	0.20	11.35
46	47	1,948	807	2,264,280	42,041	2,222,239	0.88	19.20
47	48	1,277	1,214	2,272,429	42,203	2,230,226	0.57	28.77
48	49	1,541	669	2,276,431	42,361	2,234,070	0.69	15.79
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.

(continued)

Table 6.3 (continued)

Females								
				Jan 1, 2009 population				
2009 age	2010 age	In-migr	Out-migr	U.S.	Arizona	Adjusted U.S[a]	In-migration rate[b]	Out-migration rate[c]
60	61	847	834	1,855,547	37,623	1,817,924	0.47	22.17
61	62	1,150	455	1,794,107	37,063	1,757,044	0.65	12.28
62	63	868	707	1,830,682	38,599	1,792,083	0.48	18.32
63	64	1,908	371	1,792,164	38,466	1,753,698	1.09	9.64
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
81	82	56	0	710,309	13,850	696,459	0.08	0.00
82	83	763	131	690,962	13,223	677,739	1.13	9.91
83	84	321	76	647,967	12,216	635,751	0.50	6.22
84+	85+	1,510	1,287	4,270,141	76,144	4,193,997	0.36	16.90
State total		105,262	83,316	153,374,824	3,130,988	150,243,836	0.70	26.61

Sources: U.S. Census Bureau: Maricopa County and National 2010 ACS PUMS; 2010 census; July 1, 2008 and 2009 Intercensal Estimates
[a]U.S. population − Arizona population
[b]In-migrants / adjusted U.S. population × 1,000
[c]Out-migrants / Arizona population × 1,000

or 74.85 out-migrants per 1,000 persons. Out-migration rates are much larger than in-migration rates because the denominators for out-migration rates are much smaller than the denominators for in-migration rates.

Although the rationale for constructing gross migration rates is clear, the same cannot be said for net migration rates. Because net migration is the difference between the number of in- and out-migrants, there is *no* true population at risk and rates reflecting migration probabilities cannot be constructed. We follow conventional terminology by referring to net migration ratios as "rates," but the reader is reminded that they are not rates in a probabilistic sense.

There are two basic methodological questions regarding the construction of net migration rates: (1) Should the denominator reflect the population at the beginning, middle, or end of the migration interval? and (2) Should the denominator reflect the population of the region itself or the population of some other region?

With respect to the first question, we favor using the population at the beginning of the interval as the denominator because it is unaffected by migration during the interval and corresponds to the launch-year population used for making projections. It is also common to use the beginning population "survived" to the end of the migration period using the appropriate survival rates (Irwin 1977; Pittenger 1976). This approach is a bit more complicated but has the advantage of accounting explicitly for deaths of migrants. Both approaches are acceptable and generally yield similar results. The most important thing to remember is that migration rates must be applied in a manner consistent with the way they were computed; for example, if rates were based on the unadjusted population at the beginning of the migration interval, they must be applied to the unadjusted population at the beginning of the projection interval.

The answer to the second question depends on the characteristics of the area to be projected. For regions losing population or growing fairly slowly, we favor using the population of the region itself for constructing net migration rates. For regions growing very rapidly, however, there are advantages to using the population of the rest of the country. Because there are more in-migrants than out-migrants, the rest of the country rather than the region itself is the base population for the larger number of total migrants; this provides a theoretical justification for making this choice. Perhaps more important, using the population of the rest of the country as the denominator reduces the impact of very high migration rates, which may be more realistic for projections of rapidly growing areas. Smith (1986) provides a more detailed discussion of these issues.

We illustrate the calculation of net migration rates using the same data we used for gross migration rates. For males aged 23, net migration can be calculated as:

$$4{,}508 - 3{,}290 = 1{,}218$$

This can be expressed as a rate by dividing it by the appropriate population. Using the male population aged 23 living in Arizona in 2009 as the denominator, the net migration rate can be calculated as:

$$1{,}218/43{,}956 = 0.02771$$

or 27.71 per 1,000 persons. Net migration rates can also be calculated using the population of the rest of the country as the denominator. Following this approach, the net migration rate for males aged 23 can be calculated as:

$$1{,}218/2{,}073{,}816 = 0.00059$$

or 0.59 per 1,000 persons. As noted above, we believe migration rates based on the first approach are acceptable for projections of places with slow or moderate growth rates, but the second is better for projections of rapidly growing places. When the first approach is used, migration is projected by multiplying the migration rates by the population to be projected; when the second approach is used, migration is projected by multiplying the migration rates by the national population (minus the population of the area to be projected).

6.1.1.5 International and Domestic Migration

An important distinction can be made between international (i.e., “foreign”) and domestic (i.e., “internal”) migration. International migration refers to moves from one country to another, whereas domestic migration refers to moves from one place to another within a particular country (Swanson and Stephan 2004). Although domestic migration has more impact than international migration on population growth and demographic change in most states and local areas, international migration is growing in importance and has a substantial impact in some places. People moving into a country are typically called *immigrants* and people leaving are called *emigrants*.

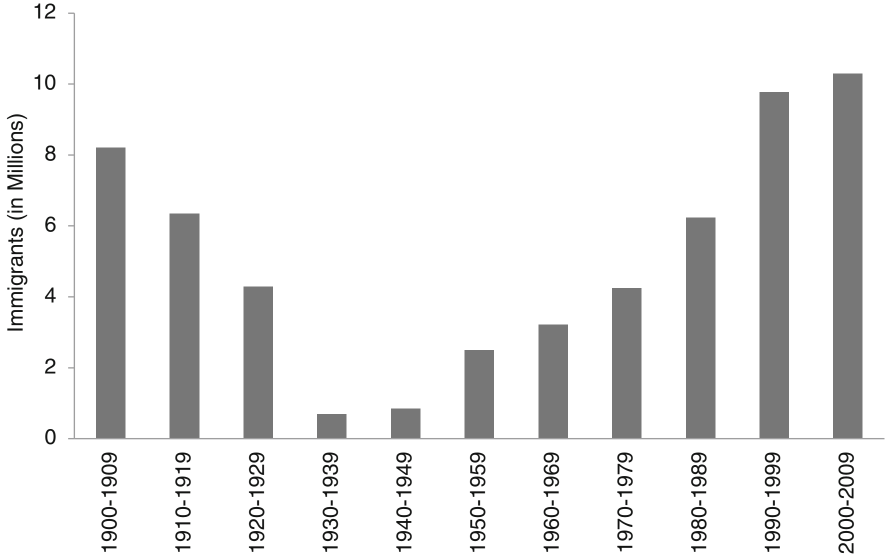

Fig. 6.1 Documented immigrants to the United States, 1900–2009 (Source: Office of Immigration Statistics 2012)

It is no exaggeration to describe the United States as a nation of immigrants. According to the Office of Immigration Statistics (2012), more than 75 million people have immigrated to the United States since 1820. The number of immigrants rose steadily throughout the nineteenth century, peaking at 8.2 million in the first decade of the twentieth century. It then started falling because of World War I and the passage of restrictive immigration laws in 1921 and 1924. The Great Depression and World War II reduced the numbers to their lowest levels since the middle of the nineteenth century. The post-war economic expansion and the easing of restrictive immigration policies led to a reversal of the downward trend and the number of immigrants has been rising steadily rising since the 1930s. The first decade of the twenty-first century saw the largest number of immigrants in the nation's history (see Fig. 6.1).

Several different categories of international migrants have been defined for the United States (Edmonston and Michalowski 2004; Judson and Swanson 2011). Technically, immigrants are citizens of other countries who have been legally admitted for residence. Refugees and asylees are persons who have been granted entry because they fear persecution for religious, political, or other reasons in their home countries; although they are not initially classified as immigrants, many later become immigrants by attaining permanent resident status. Most immigrants come to the United States for economic or family-related reasons; less than 10% come as refugees or asylum seekers (Martin and Midgley 2010). In addition, millions of foreign citizens each year are granted temporary visas to enter the country for a specific purpose, such as a vacation, a business trip, a temporary job, or to attend school. Many stay only for a few days or weeks, but others remain for many years.

Finally, there are illegal or unauthorized migrants who enter the country surreptitiously or who violate the terms of their visas. Although the number is not known exactly, it is estimated that approximately 11 million undocumented entrants were living in the United States in 2010 (Passel and Cohn 2011).

Immigrants are not evenly distributed throughout the country. More than 20% of the population is foreign-born in California, New Jersey, and New York (Grieco et al. 2012). In fact, more than a quarter of the nation's foreign-born population resides in a single state, California. Between 10% and 20% of the population is foreign-born in Arizona, Connecticut, District of Columbia, Florida, Illinois, Massachusetts, Nevada, Rhode Island, Texas, Virginia, and Washington. In comparison, less than 5% of the population is foreign-born in 19 states, with West Virginia having the smallest share at about 1%. The distribution of immigrants is even more variable for cities and counties than it is for states.

Cohort-component projections often distinguish between international and domestic migration flows because they follow different timing patterns and have different demographic and socioeconomic characteristics. Separating international from domestic migration can also have an impact on projected fertility and mortality rates because immigrants often differ from the rest of the population in terms of their fertility and mortality characteristics (Edmonston and Passel 1992; Edmonston and Michalowski 2004).

No agency in the United States collects comprehensive data on the emigration of U.S. residents to foreign countries. However, partial data are available from several sources. One is the Internal Revenue Service (IRS), which provides annual reports on the location (down to the county level) of current filers and the locations where they filed the previous year. These reports include the number of tax returns filed abroad by people residing in the United States the previous year. Another source is the U.S. Department of State. U.S. residents living abroad often register with the U.S. Embassy in the country in which they reside; although registration is not mandatory, these records provide some information on emigration. Immigration data collected by other countries can also be used to develop estimates of U.S. residents who emigrated to those countries (U.S. Census Bureau 2011a).

The number of emigrants leaving the United States has been estimated to be around 200,000 per year (Martin and Midgley 1999). Developing emigration estimates is particularly important for states and local areas that have received large numbers of immigrants in the past because emigration from the United States has been found to occur primarily among foreign-born residents (Edmonston and Passel 1992).

6.1.1.6 Assessing the Issues

Migration is a difficult concept to measure or even to define. Measures vary in their treatment of distances traveled, time intervals covered, geographic boundaries crossed, distinctions between temporary and permanent moves, and definitions of place of usual residence. We have described migration as it is typically defined in the United States, but conventional measures understate the true extent of population mobility and may distort the characteristics of migrants (Edmonston and Michalowski 2004; Judson and Swanson 2011; Morrison et al. 2004; Zelinsky 1980).

Although these shortcomings have serious implications for analyses of the determinants and consequences of migration, they do not necessarily present a problem for the construction of population projections. The objective of population projections is generally not to project the total number of moves or to classify them as temporary, permanent, repeat, return, domestic, or international. Rather, it is to project the overall impact of migration on the resident population of a particular geographic area during a particular period of time. As long as the data accurately reflect this aspect of the migration process, their inadequacies in capturing other aspects are irrelevant. The critical issues are to find data sources that accurately reflect historical migration trends and to develop realistic yet tractable models for projecting those trends into the future. We turn to these issues next.

6.2 Sources of Data

Whereas birth and death data are readily available for states and counties—and are generally considered to be quite accurate—the same cannot be said for migration data. The ideal migration data set would include at least the following (Wetrogan and Long 1990):

1. Data on both the origins and destinations of migrants.
2. Data disaggregated by age, sex, and race/ethnicity.
3. Data available in 1-year age groups.
4. Data available on an annual basis for a large number of time periods.
5. Data available on a timely basis.
6. Data consistent with the relevant population base for calculating migration rates.

In a perfect world, these data would be available for states, counties, and a variety of subcounty areas. Unfortunately, no single data set even comes close to meeting all these criteria. In fact, no central agency in the United States directly tracks population movements, as is the case in a number of European countries with population registers (see, for example, Statistics Finland 2004). Rather, migration data must be derived from a variety of sources, each with its own strengths and weaknesses.

6.2.1 Sample Surveys

6.2.1.1 American Community Survey

The American Community Survey (ACS) is a monthly survey conducted by the Census Bureau. It samples approximately 250,000 housing units each month and is designed to provide accurate and timely demographic, socioeconomic, and housing data on an annual basis for a variety of geographic areas in the United States (Citro and Kalton 2007). It provides single-year data for all states and for cities, counties, and other geographic areas with 65,000 residents or more. Data must be aggregated over several years in order to provide estimates for smaller areas. Data based on 3-year aggregations are available for places with at least 20,000 residents and data based on 5-year aggregations are available for all census-designated places, including small towns, census tracts, and block groups (U.S. Census Bureau 2009a). In 2010, the ACS replaced the long form of the decennial census as a source for detailed demographic, socioeconomic, and housing data in the United States.

As noted in Chap. 2, there are several important differences between the ACS and the long form of the decennial census. The ACS has a smaller sample size, uses different residence rules, and is based on a rolling monthly sample rather than being conducted at a single point in time. There is also an important difference regarding migration data: Whereas migration data in the decennial census were based on place of residence 5 years earlier, migration data in the ACS are based on place of residence 1 year earlier. All of these differences have important implications for the production of population projections.

The Census Bureau provides summaries of ACS migration data on its website. These summaries include in-migration data for states, counties, and subcounty areas such as cities, school districts, zip code tabulation areas, census tracts, and block groups. They include breakdowns by age, sex, race, and several other characteristics but do not include cross tabulations of one characteristic by another (e.g., age by sex). Summaries of out-migration data are not a part of regular ACS products, but the Census Bureau has produced a series of reports showing in- and out-migration data for counties and county equivalents (Benetsky and Koerber 2012). These reports include a limited amount of data on the characteristics of migrants but do not include any cross tabulations.

More detailed characteristics are available from Public Use Microdata Sample (PUMS) files. These files contain records for individual people and housing units and can be tabulated in a variety of ways. Individual records have been stripped of all identifying information and represent about 1% of the population. PUMS files are available only for areas with at least 100,000 residents, which excludes 81% of counties and the vast majority of subcounty areas in the United States (U.S. Census Bureau 2011b).

6.2.1.2 Current Population Survey

The Current Population Survey (CPS) is a monthly survey of about 60,000 households conducted by the Census Bureau for the Bureau of Labor Statistics (http://www.census.gov/cps/). Begun in 1940, the CPS was designed primarily to obtain labor force information but questions on socioeconomic and demographic characteristics (including geographic mobility) were added in 1947 (U.S. Census Bureau 2006). Unlike the ACS, the CPS uses the traditional census definition of residence and has a "point-in-time" orientation, making its data more consistent with the decennial census than is true for the ACS. Furthermore, although the migration question in the CPS is based on place of residence 1 year ago, the survey instrument also includes a 5-year migration question in years ending in 0 and 5, making it possible to construct 5-year migration rates consistent with rates based on data from previous decennial censuses (Ihrke and Faber 2012).

Every spring (primarily in March), CPS interviewers ask questions on migration and many other topics in the Annual Social and Economic Supplement. Because of the small sample size, however, migration data are tabulated and released only at the national and regional levels. Data on the number and characteristics of migrants have been available since 1947 but questions on reasons for moving were added only in 1998. In addition to regularly tabulated statistics, individual micro-data files (similar to PUMS files) can be accessed to create customized cross tabulations (U.S. Census Bureau 2006).

6.2.1.3 Other Surveys

Other surveys that have been used to study mobility and migration include the American Housing Survey, the Survey of Income and Program Participation, and the General Social Survey. These surveys provide data that are useful for some types of analyses, but generally do not provide a sufficient basis for projecting state and local migration because of their small sample sizes, the nature of their sampling frames, the definitions of mobility and migration they use, and the levels of demographic and geographic detail they provide.

6.2.2 Administrative Records

Administrative records kept by federal government agencies provide another source of migration data. Three agencies of particular importance for our purposes are the Internal Revenue Service (IRS), Office of Immigration Statistics (OIS), and U.S. Postal Service (USPS).

6.2.2.1 Internal Revenue Service

By matching the addresses listed on annual income tax returns and adjusting for the number of exemptions claimed on each return, the Census Bureau has created an annual set of state-to-state and county-to-county migration flows. These data have one important advantage over ACS migration data: Because they are based on a much larger number of individual records, they are more reliable (i.e., smaller sampling error) than ACS migration data.

IRS migration data have several limitations, however. Not everyone files an income tax return; in particular, people with low incomes are not required to file. People moving to or from abroad are often missed. The address listed on a tax return may be that of a bank, law office, accounting firm, or post office box rather than the home address of the filer; this may lead to an inaccurate distribution of the population at the local level. The methodology assumes that people listed as exemptions on a tax return actually live (and move) with the filer; this may not be true. Finally, IRS migration data provide no information on the demographic characteristics of migrants and are not available below the county level.

In spite of these problems, IRS data provide useful information on annual migration flows for states and counties. They cover more than 90% of the U.S. population and provide migration estimates that remain relatively stable over time. IRS data have been used by the Census Bureau for the production of population estimates since the 1970s and for the production of population projections since the 1980s. For further discussion of the strengths and weaknesses of IRS migration data, see Engels and Healy (1981), Gross (2005), Isserman et al. (1982), and Wetrogan and Long (1990).

6.2.2.2 Office of Immigration Statistics

Official immigration statistics in the United States have been collected each year since 1820 (Edmonston and Michalowski 2004). These data were compiled by several different federal agencies until 1892, when this function was transferred to the Immigration and Naturalization Service (INS) in the Department of Justice. In 2002, it was transferred to the newly formed Office of Immigration Statistics (OIS) in the Department of Homeland Security.

The OIS produces annual statistics on the number of legal immigrants by type, country of origin, place of intended residence, age, sex, marital status, occupation, and several other characteristics. These statistics, however, are based on the year in which a person was granted legal immigration status, which is not necessarily the same as the year in which that person entered the country. Furthermore, they exclude estimates of undocumented immigrants, which fluctuate from year to year but were estimated at approximately 11 million in 2010 (Passel and Cohn 2011). Although the federal government started keeping records on emigration in 1908, they were discontinued in 1957 (Edmonston and Michalowski 2004). As mentioned previously, emigration estimates can be developed using demographic analysis and several administrative and census data sources.

6.2.2.3 U.S. Postal Service

The U.S. Postal Service (USPS) compiles data on changes of address through its National Change of Address (NCOA) service (Martins et al. 2011). Groups that subscribe to this service can obtain updates when a postal customer files a change-of-address form with the Postal Service. This data source is particularly useful for monitoring small-area population changes and is one of the primary methods private companies use to obtain change-of-address information for individuals. Businesses can purchase the updates for as little as $5 per one thousand names.

6.2.2.4 The Private Sector

Thomas, Gould and Stillwell (2012) evaluated data available from a private company (Axciom) as a potential alternative to administrative records and surveys as a source of migration estimates in England. These estimates were based on data from an annual lifestyle survey done by this company. In addition, Axciom has other types of data that can be used for estimating migration, including the NCOA data compiled by the USPS (Martins et al. 2011). These data include length of residence at the current location and many other variables. Records can be sorted and aggregated to obtain migration flows by area, including information of a variety of individual and household characteristics. Other companies (e.g., Experian) provide similar services.

6.2.3 *Indirect or Residual Estimates of Migration*

The sources discussed above provide data on gross migration, or unidirectional population moves into or out of a region. Estimates of net migration can be derived from these gross migration data by subtracting the number of out-migrants from the number of in-migrants. For example, Table 6.2 shows net migration calculated in this manner for states. There are many circumstances, however, in which gross migration data are not available. Under these circumstances, indirect estimates of net migration can be made by comparing a region's population at two points in time, measuring the change due to natural increase, and attributing the residual to net migration. Several different methods can be used to calculate net migration in this manner.

One is the *vital statistics method*, in which net migration (NM) is calculated by rearranging the terms of the demographic balancing equation described in Chap. 2:

$$\mathrm{NM} = \mathrm{P_l} - \mathrm{P_b} - \mathrm{B} + \mathrm{D}$$

where P_l is the population in a given year, P_b is the population in some earlier year, and B and D are the number of births and deaths that occurred between times b and l. For example, Seminole County, Florida had a population of 365,199 in 2000 and 422,718 in 2010. It recorded 46,451 births and 27,173 deaths between 2000 and 2010. Net migration during the decade therefore can be estimated as:

$$38{,}241 = 422{,}718 - 365{,}199 - 46{,}451 + 27{,}173$$

The vital statistics method can be used to calculate net migration for the entire population or for subgroups of the population (e.g., racial groups). However, the process is very cumbersome when applied to demographic subgroups (especially classified by age) and requires collecting a great deal of data, which are frequently unavailable for subcounty areas. To avoid these problems, a second residual method is often used.

This is called the *survival rate method*. Instead of accounting for births and deaths explicitly, this method uses life table survival rates to estimate the expected population in each subgroup at the end of the period. Estimates of net migration are then calculated as the difference between the expected population and actual population. The most common form of this method is the *forward survival rate method* (FSRM), in which net migration is estimated as:

$$\mathrm{NM} = {}_{\mathrm{n}}\mathrm{P}_{\mathrm{x+y,l}} - \left({}_{\mathrm{x}}\mathrm{S}_{\mathrm{n}}\right)\left({}_{\mathrm{n}}\mathrm{P}_{\mathrm{x,b}}\right)$$

where ${}_nP_{x,b}$ is the population age x to $x + n$ in year b, ${}_nP_{x+y,l}$ is the population age $x + y$ to $x + n + y$ in some later year l, y is the number of years between b and l, and ${}_xS_n$ is the y-year survival rate for age group x to $x + n$. For example, Florida had 115,768 Hispanic males aged 20–24 in 2000, 162,331 Hispanic males aged 30–34 in 2010, and a 10-year survival rate of 0.9851, yielding a net migration estimate of:

$$48{,}288 = 162{,}331 - (0.9851)\,(115{,}768)$$

This method can be applied to every subgroup in the population to provide net migration estimates for a number of demographic categories.

The reverse survival rate method (RSRM) can also be used. Under this approach, the current population in a given subgroup is "reverse survived" back to the preceding census; that is, the reciprocal of the survival rate is applied. The difference between the survivors and the earlier census count is calculated as the estimate of net migration. Either of these approaches—or a combination of the two—can be used to estimate net migration (Siegel 2002, p. 22). More detailed discussions of these methods and other indirect estimates of net migration can be found in Morrison et al. (2004) and Rogers et al. (2010).

The major advantage of indirect methods of estimating net migration is that they can be applied when no direct data on in- and out-migration are available. Consequently, they are particularly useful for projections of small areas. However, the accuracy of these estimates depends on the accuracy of the underlying population estimates (or counts) and the vital statistics (or survival rate) data. Vital statistics and survival rate data in the United States are generally quite accurate, but the accuracy of population estimates and census counts varies over time and from place to place. In particular, changes in undercount (or overcount) from one census to another may cause decadal estimates of net migration to be too high or too low. This is seldom a problem for larger areas, but may be an issue for small areas (e.g., census tracts or block groups). Changes in geographic boundaries may also affect net migration estimates; again, this generally will not be a problem for states and counties, but may be significant for cities, census tracts, zip code areas, and other subcounty areas.

Estimates of net migration by age, sex, and race for states were produced for each decade from 1870 to 1950 (Kuznets et al. 1957). These estimates were extended to counties for each decade from 1950 to 2010 (Winkler et al. 2013). Because net migration estimates by age, sex, and race/ethnicity are not available for most subcounty areas, analysts making subcounty projections may have to start by producing those estimates themselves.

It should be noted that residual estimates of net migration are consistent with the time frame and residency rules used in the decennial census. Moreover, they can be developed for any level of geography for which birth, death, and census data are reported. Both of these advantages make residual estimates quite useful for cohort-component population projections, especially for small areas.

We close this section by briefly mentioning the model-based migration estimates developed by Rogers et al. (2010). This approach emphasizes three general areas: (1) smoothing existing data that are irregular; (2) repairing existing data that are defective; and (3) inferring migration where no (valid) data are available. Most of the examples deal with out-migration flows and rates, but the techniques they describe could be applied to in-migration flows and rates and even to net migration, although defining denominators for migration rates would be a challenge. The basic strategy they describe is to use all available information, with the aim of generating age- and spatially-related patterns. Although the assumptions and techniques are too complex to discuss here, the loss of long-form migration data makes the development of model-based estimates particularly attractive.

6.3 Evaluating and Adjusting ACS Migration Data

6.3.1 Evaluating ACS Data

The ACS has replaced the long form of the decennial census as the primary source of detailed migration data in the United States. As noted previously, there are several differences between the ACS and the census long form: The ACS is based on a rolling sample rather than a single point in time, uses different residence rules, has a smaller sample size, and measures migration over a 1-year interval rather than a 5-year interval. Furthermore, the Census Bureau does not plan to release as much detailed migration data from the ACS as it did from the decennial census. All these differences have implications for the calculation of migration rates and the construction of cohort-component population projections.

The rolling sample changes the interpretation of migration data. In the decennial census, migration data were based on a specific time period: place of residence 5 years ago (e.g., April 1, 1995 for the 2000 census). In the ACS, migration data are based on place of residence 1 year prior to the month in which a person responds to the survey. One-year data are derived from all surveys conducted over a 12-month period, 3-year data are derived from all surveys conducted over a 36-month period, and 5-year data are derived from all surveys conducted over a 60-month period. This is not necessarily a problem, but it changes the interpretation of the migration data and complicates the construction of migration rates (e.g., what is the appropriate measure of the population at risk?).

The decennial census attempts to count people at their usual place of residence whereas the ACS counts people who live at a particular address for at least 2 months. This difference most likely has little impact on the data collected in most places, but may have a significant impact in places with large numbers of seasonal and other temporary residents (e.g., snowbirds in Florida and Arizona). Few studies have evaluated this impact, but there is some evidence that significant differences exist for some variables (Swanson and Hough 2012; van Auken et al. 2006). Further research is needed before we can fully evaluate the impact of differences in residence rules on the migration data collected in the ACS.

The collection of 1-year rather than 5-year migration data affects the construction of migration rates. It is difficult to transpose 1-year migration data into 5-year data; as a result, projections based on ACS migration rates will generally have to use single-year age groups and 1-year projection intervals. This can be a problem because 1-year migration rates are more strongly affected by short-run fluctuations in economic conditions and by the impact of unique events than are 5-year rates; this volatility raises the level of uncertainty for long-range population forecasts. This problem can be reduced by using data collected over a 5-year period, but cannot be eliminated completely. Furthermore, migration rates vary more across single-year age groups than 5-year age groups because they are based on smaller populations. This contributes to inconsistencies in age-specific migration rates, as illustrated in the following section.

The smaller sample size of the ACS is particularly important. Even when aggregated over a 5-year period, the sample size for the ACS is considerably smaller than the sample size for the long form of the decennial census. This makes ACS migration data less reliable (i.e., larger sampling error) than migration data from decennial censuses, especially for demographic subgroups and geographic areas with small populations.

A final difference between the ACS and the decennial census is the reduction in migration data products released by the Census Bureau. In previous decades, the Census Bureau released a complete set of in- and out-migration data by age, sex, and race for states and counties. Under current plans, the Census Bureau will be releasing a more limited set of migration data products based on the ACS (Benetsky, M., 2013, Personal communication). Specifically, it will release in- and out-migration data for counties, broken down by three characteristics each year (e.g., age, sex, and marital status). The data will not be cross tabulated and the characteristics will change from year to year. As a result, more detailed demographic data (e.g., in- and out-migration broken down by age, sex, and race simultaneously) will have to be derived from PUMS files or created by combining data sets.

Clearly, there are major differences between the ACS and the long form of the decennial census. An important advantage of the ACS is its frequency and timeliness: Data are released on an annual basis throughout the decade rather than only once following a decennial census. An important disadvantage is its smaller sample size, which reduces the reliability of the data. This creates a problem for the construction and application of migration rates, particularly for small areas. How can this problem be dealt with?

6.3.2 Adjusting ACS Data

Figure 6.2 shows raw (i.e., unadjusted) in- and out-migration rates from 2009 to 2010 for males and females by single year of age in Arizona. These rates are based on the same data and procedures shown in Table 6.3.

The expected migration patterns are clearly visible. Both in- and out-migration rates are highest for people in their twenties and early 30s and decline thereafter, except for an increase in in-migration rates for people in their 60s. However, the rates fluctuate wildly from one age group to another and show many irregularities. For example, in-migration rates for males in the youngest age groups differ substantially from rates for females; one would expect them to be about the same because young children typically move with their parents. There is a tremendous spike in the out-migration rate for females at age six; again, there is no reason to expect this to be true. Above age 70, in-migration rates for males are much higher than rates for females in some age groups and much lower in others. Similar irregularities are found at other ages throughout the age distribution. These patterns stand in sharp contrast to research showing that migration rates normally change fairly smoothly over the age distribution (Rogers et al. 2010).

These fluctuations and irregularities are caused primarily by the small sample size. One potential solution to this problem is to use 5-year ACS data rather than data from a single year (Mather et al. 2005; Griffin and Waite 2006). This will raise the sample size considerably, thereby improving the reliability of the data. However, it will not solve the problem completely, especially for demographic subgroups and geographic areas with small populations. Furthermore, using 5 years of data makes it impossible to measure changes in annual migration patterns (Franklin and Plane 2006).

Another potential solution is to adjust the migration data. This can be done using nonlinear smoothing techniques (Vellman 1980). We apply two techniques, one based on three observations (Smooth 3) and one based on five observations (Smooth 5). The results for in-migration rates for males are shown in Fig. 6.3, along with the original rates shown in Fig. 6.2. Although the smoothing techniques greatly reduce the fluctuations, many irregularities are still apparent, such as the large jump between ages 17 and 18 and the noticeable plateauing at several age groups.

We believe a better solution can be achieved by following a three-step adjustment process (Rogers et al. 2010). First is to aggregate single-year age

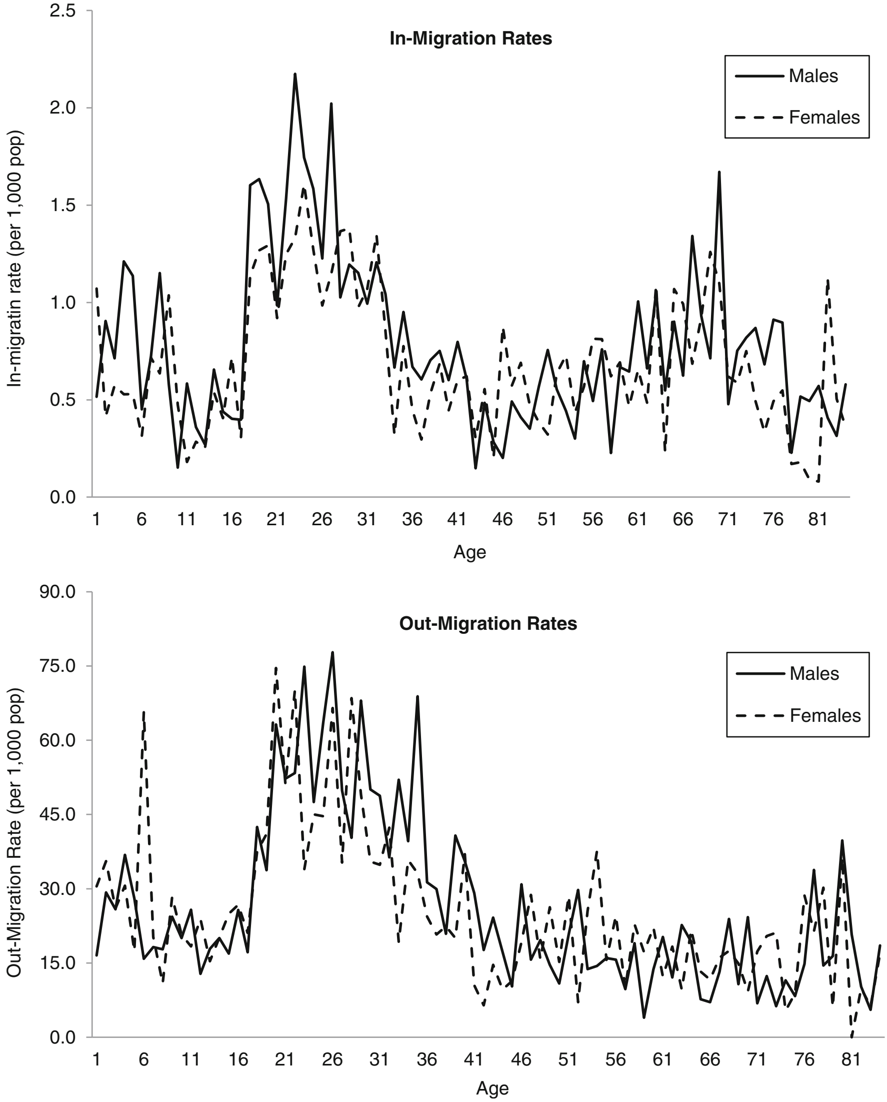

Fig. 6.2 Single year in- and out-migration rates by sex, Arizona, 2009–2010

data into broader age groups. Aggregating the data reduces many (but not all) of the wildly fluctuating migration patterns found in the single-year age data. Second is to construct in- and out- migration rates for these broader age groups in the manner described previously. Third is to use interpolation procedures to create single-year rates from the rates for broader age groups developed in the second step. We illustrate this process using the migration data for Arizona shown in Fig. 6.2.

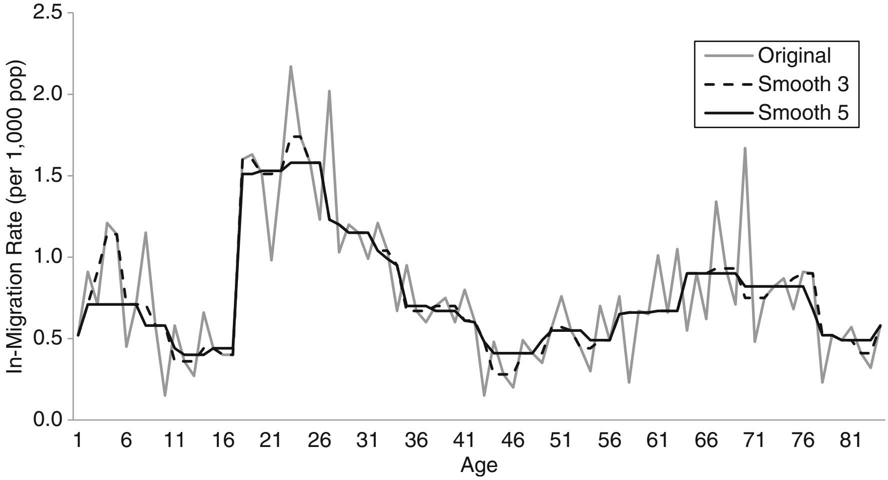

Fig. 6.3 Smoothed single-year in-migration rates for males, Arizona, 2009–2010

Table 6.4 shows the first two steps in the process. Migration data by single year of age were aggregated into broader age groups (in some instances, they also were adjusted to account for apparent anomalies and inconsistencies). These numbers were then divided by the relevant populations to provide a set of in- and out-migration rates. These rates are considerably more consistent across age groups and between sexes than those shown in Fig. 6.2.

The final step of the adjustment process is to transpose the migration rates for broader age groups back into rates by single year of age. This can be done using any one of a number of interpolation methods, as described in Chap. 10. In this instance, we used the cubic spline method, which we believe generally gives superior results (McNeil et al. 1977). The results for females are shown in Fig. 6.4.

The target rates are those shown for 5-year age groups in Table 6.4. The rates for single-year age groups are represented by the smooth lines. The single-year rates follow the pattern implied by the spline target rates very well and the age patterns are much smoother than those shown in Fig. 6.2. We believe the adjustment techniques described here will generally lead to more reliable migration rates than could be obtained using unadjusted data; these improvements will be particularly substantial when rates are calculated for racial/ethnic groups and for geographic areas with small populations.

Rogers et al. (2010) suggest an additional step that might further improve age-specific migration rates from the ACS; namely, fitting model migration schedules to the splined age profiles. MATLAB programming code for estimating the parameters of such migration models can be found on the website of the Institute of Behavioral Science at the University of Colorado (http://www.colorado.edu/ibs/pop/indirect_estimation_of_migration/scripts/model_migration_schedules.html).

Table 6.4 Domestic migration rates by 5-year age group and sex, Arizona, 2009–2010

2009 age	2010 age	In-migrants	Out-migrants	Jan 1, 2009 population U.S.	Jan 1, 2009 population Arizona	Jan 1, 2009 population Adjusted U.S[a]	In-migration rate[b]	Out-migration rate[c]
Males								
1–4	2–5	7,442	6,249	8,215,817	185,698	8,030,119	0.93	33.65
5–9	6–10	7,154	5,846	10,277,883	228,524	10,049,359	0.71	25.58
10–14	11–15	5,407	4,506	10,466,060	226,299	10,239,761	0.53	19.91
15–19	16–20	9,339	7,332	11,182,079	234,487	10,947,592	0.85	31.27
20–24	21–25	14,891	12,030	10,895,703	226,860	10,668,843	1.40	53.03
25–29	26–30	14,992	11,965	10,521,190	222,952	10,298,238	1.46	53.67
30–34	31–35	11,428	9,626	9,888,975	209,726	9,679,249	1.18	45.90
35–39	36–40	8,426	6,568	9,934,005	207,750	9,726,255	0.87	31.61
40–44	41–45	6,632	5,464	10,282,175	203,475	10,078,700	0.66	26.85
45–49	46–50	5,390	4,335	11,088,515	209,997	10,878,518	0.50	20.64
50–54	51–55	5,166	3,551	10,815,671	200,029	10,615,642	0.49	17.75
55–59	56–60	4,320	3,075	9,421,208	176,562	9,244,646	0.47	17.42
60–64	61–65	5,634	2,511	7,990,616	164,988	7,825,628	0.72	15.22
65–69	66–70	3,924	1,668	5,789,595	132,026	5,657,569	0.69	12.63
70–74	71–75	2,606	1,328	4,198,322	101,420	4,096,902	0.64	13.09
75–79	76–80	1,844	1,045	3,148,158	75,323	3,072,835	0.60	13.87
80–83	81–84	970	540	1,900,577	42,876	1,857,701	0.52	12.59
84+	85+	1,030	688	2,139,545	45,320	2,094,225	0.49	15.18
State total		116,595	88,327	148,156,094	3,094,312	145,061,782	0.80	28.54
Females								
1–4	2–5	7,340	6,824	7,866,939	177,846	7,689,093	0.95	38.37
5–9	6–10	6,822	6,250	9,852,416	219,469	9,632,947	0.71	28.48
10–14	11–15	4,762	4,060	9,989,249	216,741	9,772,508	0.49	18.73
15–19	16–20	7,756	6,595	10,621,749	221,313	10,400,436	0.75	29.80
20–24	21–25	12,799	10,981	10,458,660	210,183	10,248,477	1.25	52.24
25–29	26–30	12,198	10,469	10,354,225	211,532	10,142,693	1.20	49.49
30–34	31–35	8,917	7,614	9,858,926	201,746	9,657,180	0.92	37.74
35–39	36–40	6,597	5,414	10,029,105	202,729	9,826,376	0.67	26.71
40–44	41–45	5,472	4,180	10,384,626	198,224	10,186,402	0.54	21.09
45–49	46–50	5,279	3,974	11,376,413	211,663	11,164,750	0.47	18.78
50–54	51–55	5,595	3,874	11,243,200	210,272	11,032,928	0.51	18.42
55–59	56–60	4,734	2,884	10,032,606	193,983	9,838,623	0.48	14.87
60–64	61–65	5,810	2,613	8,646,865	181,552	8,465,313	0.69	14.39
65–69	66–70	4,023	2,243	6,512,253	147,277	6,364,976	0.63	15.23
70–74	71–75	2,442	1,651	4,980,307	110,899	4,869,408	0.50	14.89
75–79	76–80	1,816	1,385	4,091,142	84,893	4,006,249	0.45	16.31
80–83	81–84	1,164	972	2,806,002	54,522	2,751,480	0.42	17.83
84+	85+	1,736	1,333	4,270,141	76,144	4,193,997	0.41	17.51
State total		105,262	83,316	153,374,824	3,130,988	150,243,836	0.70	26.61

Sources: U.S. Census Bureau: Arizona and National 2010 ACS PUMS; July 1, 2008 and 2009 Intercensal Estimates

[a] U.S. population − Arizona population

[b] In-migrants / adjusted U.S. population × 1,000

[c] Out-migrants / Arizona population × 1,000

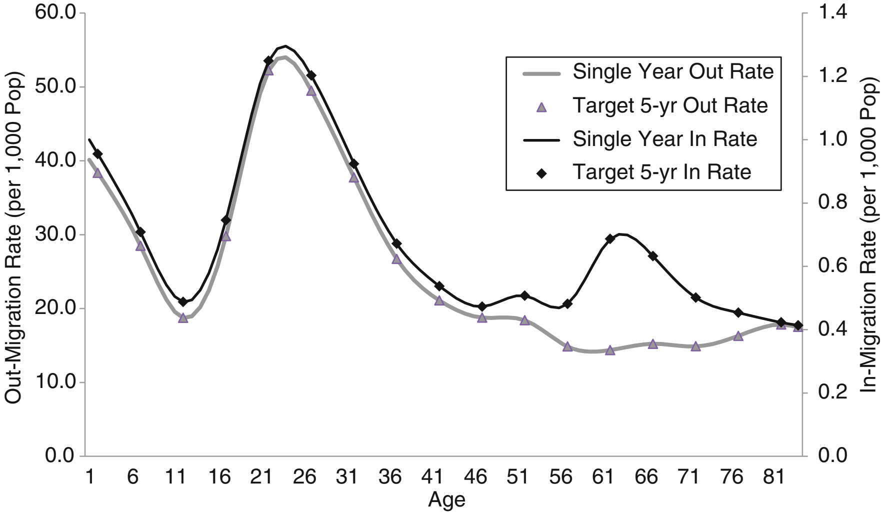

Fig. 6.4 Interpolated single year female in- and out-migration rates, Arizona 2009–2010

The replacement of the census long form by the ACS presents a number of challenges for the producers of population projections, but provides some benefits as well. Migration researchers and other data analysts are just now starting to come to grips with this new data source and will undoubtedly come up with ways to maximize its usefulness and minimize its shortcomings. The three-step adjustment process described here is one step in that direction. We expect that future research will lead to additional improvements.

6.4 Determinants of Migration

Why do people move? How do they decide when and where to move? Perhaps more important for population projections, why do some areas have more people moving in than out while others have more moving out than in? What causes an area's migration patterns to change over time? It is helpful to consider some possible answers to these questions before attempting to construct projections of future migration flows. Although we cannot provide a complete discussion of the determinants of migration in this chapter, we can point out some of the theoretical perspectives and empirical findings that are particularly relevant to population projections. More complete discussions can be found elsewhere (Greenwood 1997; Lee 1966; Long 1988; Massey et al. 2002; Morrison et al. 2004; White and Lindstrom 2005; Zelinsky 1980).

6.4.1 Theoretical Foundations

Studies of the determinants of migration are often based implicitly or explicitly on the theory of utility maximization (Cushing and Poot 2004; DaVanzo and Morrison 1981; Greenwood 1997; Hunt 1993; Lee 1966; Molloy et al. 2011). The basic idea is that each person (or household) considers all the advantages and disadvantages of living at the current location, the advantages and disadvantages of living at all other possible locations, and the full costs of moving from one location to another (i.e., money, time, and psychic costs). If the person (or household) determines that moving would raise the overall level of utility by more than the cost of the move, the decision to move is made, presumably to the location that will yield the greatest gain in utility. Although terminology and areas of emphasis vary from study to study, this basic theoretical foundation has been used by migration researchers in economics, sociology, anthropology, geography, and other disciplines.

An alternative to the theory of utility maximization was provided by Massey et al. (2002). Their approach was originally applied to international migration but applies to domestic migration as well. It was developed because of the inability of utility maximization theory to explain why specific origin-destination migration flows persist in the face of changing economic conditions in the origin and destination communities. It is based on the idea of social capital, which is created when the relations among persons change in ways that facilitate action (Coleman 1990). Massey and his colleagues apply this theory to chain migration, arguing that each act of migration creates social capital among people to whom the migrant is related, thereby raising the odds of their migration. These chains are essentially networks of social reciprocity, knowledge, and skills. In this approach, once the number of network connections reaches a critical threshold, migration becomes self-sustaining and tends to operate beyond the boundaries of utility maximization in a narrowly economic sense.

As this brief discussion suggests, many factors influence decisions regarding whether, where, and when to move. Some are personal characteristics such as age, education, marital status, health status, occupation, social/psychological ties to the community, and perceptions of risk. Others are characteristics of various locations, including labor market conditions (e.g., wages, unemployment rates, rates of job creation), costs of living (e.g., state and local taxes, land and housing prices), and amenities (e.g., climate, topography, air and water quality, cultural and recreational opportunities, availability of public goods). Moving costs—including opportunity and information costs as well as direct out-of-pocket expenses—are also important. An individual or household weighs all these factors when making migration decisions.

Migration decisions also are strongly affected by one's passage through the stages of the life cycle (Goldscheider 1971; Pittenger 1976; White and Lindstrom 2005). Young children typically move with their parents, often with little input into the migration decision. In early adulthood, young people move out of their parents' homes to establish their own households, attend college, enter military service, and

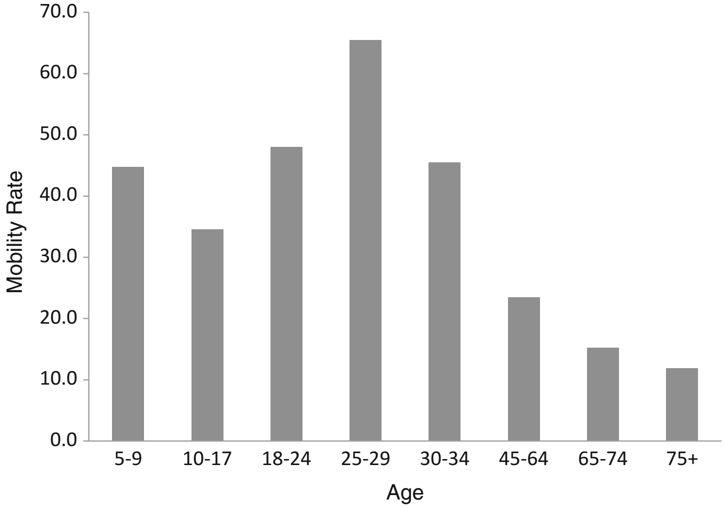

Fig. 6.5 Mobility rates by age, United States, 2005–2010 (Source: Ihrke and Faber 2012)

so forth. Moves are frequent for young adults as they embark upon their careers, get married, get divorced, establish families, and seek better housing. Moves become less frequent as age increases, but still occur in response to changes in economic conditions, job status, marital status, family size, neighborhood characteristics, and social networks. Retirement from the labor force provides a new opportunity to move, perhaps to an area with a warmer climate or a different mix of amenities. Finally, declining health or the death of a spouse may induce additional moves in the latter years of life.

These life cycle influences are clearly reflected in age-specific mobility and migration rates. As shown in Fig. 6.5, mobility rates in the United States are relatively high at ages 5–9, considerably lower at ages 10–17, increase dramatically for people in their twenties, and decline steadily thereafter. These are typical patterns found in many countries, in different regions within the same country, and at various levels of geography. These patterns tend to persist over time and from place to place even though overall migration levels may vary considerably. They are so pervasive that model migration schedules have been developed to summarize and codify their regularities (Pittenger 1976; Plane 1993; Rogers and Castro 1984; Rogers et al. 2010).

These age patterns are consistent with one version of the theory of utility maximization, in which migration is viewed as an investment in human capital that entails costs and produces benefits (Clark 1986; DaVanzo and Morrison 1981; Greenwood 1997; Sjaastad 1962). People will migrate if the present value of all future gains in benefits outweighs the full cost of migration. After a person has entered the labor force, further increases in age reduce the remaining number of years over which to reap the benefits of migration; consequently, migration rates would be expected to decline as age increases. That is precisely what the empirical evidence shows. Because this cost-benefit view implies that people will move to the areas that maximize their net benefits, it also provides a basis for projecting regional migration flows. We return to this idea in our discussion of structural models in Chap. 9. These age-related patterns are also consistent with the ideas of social capital and chain migration mentioned previously.

Not every state or local area fits this “typical” age pattern, of course. Places with universities or military installations may have larger numbers of young adult migrants than is ordinarily the case. Regions with depressed economies may have unusually large outflows of young adults. Retirement communities may have unusually large inflows of older adults. The unique characteristics of each state and local area must be considered when developing the assumptions that will be used for projecting migration rates.

6.4.2 Reasons for Moving

There are two basic approaches to studying reasons for moving (Lichter and DeJong 1990). One is simply to ask movers about their reasons for moving. According to the CPS, about 29% of movers in the United States in 2011–2012 cited family reasons (e.g., change in marital status, establish one’s own household), 49% cited housing reasons (e.g., bigger house, better neighborhood), 19% cited employment reasons (e.g., job transfer, take a new job), and 3% cited some other reason (U.S. Census Bureau 2012d). It should be noted that family and housing reasons are often closely related; for example, an increase in family size may lead to a desire for a larger house or apartment. Consequently, distinctions between family and housing reasons for moving are somewhat blurred.

These numbers were strongly affected by the behavior of local movers because they constitute the majority of movers in the United States. Housing and family reasons are by far the most important motives for local moves, with employment reasons falling far behind (Lichter and DeJong 1990). For intra-county movers in 2011–2012, for example, 59% moved for housing reasons, 30% for family reasons, and only 10% for employment reasons.

For longer distance moves, however, employment-related reasons predominate. Table 6.5 shows reasons for moving for all movers crossing county boundaries between 2011 and 2012, by distance of move. Housing reasons accounted for 43% of moves of less than 50 miles but only 22% of moves of more than 500 miles. Employment reasons, on the other hand, accounted for 24% of moves of less than 50 miles but for 52% of moves of more than 500 miles. Family reasons also declined as the distance of the move increased, but the changes were not as large as for the other two sets of reasons. These results suggest that analysts should pay special attention to local housing trends when making projections for very small areas (e.g., census tracts, block groups) and should consider the potential impact of changing economic conditions when making projections for large areas (e.g., states, metropolitan areas).

Table 6.5 Reasons for moving by distance, United States, 2011–2012[a]

	Miles				
Reason	<50	50–199	200–499	500+	U.S. total
Family					
Number	1,458	700	391	700	3,249
Percent	30.6	28.6	24.1	23.2	27.4
Employment					
Number	1,128	911	783	1,568	4,390
Percent	23.7	37.3	48.2	52.0	37.1
Housing					
Number	2,063	770	394	672	3,899
Percent	43.3	31.5	24.3	22.3	32.9
Other					
Number	114	63	55	73	305
Percent	2.4	2.6	3.4	2.4	2.6
Total					
Number	4,763	2,444	1,623	3,013	11,843
Percent	100.0	100.1	100.0	100.0	100.0

Source: U.S. Census Bureau, 2012 Current Population Survey, Annual Social and Economic Supplement, Table 27
[a]Data are for county-to-county movers

Reasons for moving vary considerably by age. In one study, job transfers, looking for work, or taking a new job were the primary reasons for moving for more than half the interstate migrants less than age 50 (Long 1988). Employment-related reasons started to decline in importance around age 50, and for persons older than age 65 they accounted for only a tiny proportion of interstate moves. Climate, on the other hand, became increasingly important at older ages. Although it accounted for less than 5% of interstate moves for persons less than age 50, seeking a change in climate accounted for 13–15% of the moves for persons aged 50–64 and 30% for persons aged 65–69 (Long 1988). Health considerations also have a much larger impact on migration decisions for older persons than younger persons (Rogers 1992). Changes in the age distribution of the population may therefore lead to substantial changes in migration patterns, especially for some states and local areas (e.g., retirement areas).

Survey data on reasons for moving provide valuable insights into migration behavior, but have several limitations (Lichter and DeJong 1990; Long 1988). Some respondents may not know exactly why they moved or may not be able to describe their reasons clearly. Some may be unable to disentangle and prioritize within a web of multiple reasons. Some may lie, mislead, or rationalize regarding their true motives. Others may simply forget. Indeed, one study reported that only 54% of migrants gave the same primary reason for moving both before and after the move (McHugh 1985). Survey data help analysts formulate their assumptions regarding future migration behavior, but do not provide definitive answers.

A second way to determine why people move is to infer motives using statistical analyses of migration behavior. Under this approach, analysts seek to uncover systematic relationships between migration and personal characteristics (e.g., age, education, marital status) and/or regional characteristics (e.g., wage rates, unemployment rates, amenities). Studies of individual behavior typically find age to be the most important predictor of mobility (Gober 1993; Long 1988; Molloy et al. 2011; White and Lindstrom 2005). Education has also been found to be important, as people with higher levels of education generally have higher migration rates than people with lower levels, especially for long-distance moves (Greenwood 1997; Long 1988; Molloy et al. 2011). For strictly local moves, however, people with higher levels of education have been found to have lower mobility rates than people with lower levels (Ihrke and Faber 2012). Being married and having children living at home tends to reduce the probability of moving (Greenwood 1997). Renters are considerably more mobile than homeowners, both with respect to local mobility (Ihrke and Faber 2012) and long-distance migration (Molloy et al. 2011).

Structural models may also be developed with migration as the dependent variable and various characteristics of migrants and/or the areas of origin and destination as independent variables. The theoretical basis of these models is frequently the concept of utility maximization, as described above. Empirically, they can be tested using data at the individual or household level (Clark et al. 1996; DaVanzo 1983; Graves and Linneman 1979; Morrison 1971) or using aggregate data for counties, states, or other geographic areas (Clark and Hunter 1992; Coulombe 2006; Foot and Milne 1989; Greenwood and Hunt 1989). Structural models not only add to our understanding of the determinants of migration, but also help explain why some states and local areas are growing faster than others and why their migration levels are increasing or declining over time. Results generated by these models can be incorporated into population projection models to provide projections that are consistent with various theories of migration or with alternative scenarios regarding changing economic conditions. We discuss structural models in Chap. 9.

6.5 Migration Models

We have now described a number of concepts, measures, definitions, data sources, and theoretical approaches used in the analysis of migration. We turn next to the construction of migration models that can be used for cohort-component population projections. We begin with models using gross migration data and close with models using net migration data. The gross migration models focus on domestic migration; projections of international migration are handled separately. The net migration models combine the effects of domestic and international migration.

6.5.1 Gross Migration

We discuss two basic approaches to projecting gross migration in cohort-component models. The first is based on historical data on in- and out-migration without reference to the places of origin and destination of those migrants; the second is based on data covering specific place-to-place migration flows. Both approaches were developed to provide a consistent set of projections for a large number of places, such as all the states in the United States or all the counties in a state. Both approaches also require a great deal of base migration data and a large number of calculations. We also discuss simplified versions of both approaches that retain a number of their useful features but require less data and fewer calculations. Our examples are based on 5-year migration intervals and 5-year age groups because those have been the most commonly used over the last several decades. The same approaches could also be used for single-year intervals and age groups; these will become more common as ACS data replace migration data collected in the long form of the decennial census.

6.5.1.1 Migrant Pool Models

The first approach is based on the application of out-migration rates and in-migration proportions for each region to be projected. This approach was used by the Census Bureau for several sets of state population projections (U.S. Census Bureau 1966, 1972, 1979). We describe it using a hypothetical example of state projections, with 2000 as the launch year.

To begin, out-migration rates by age and sex are calculated for each state using 1995–2000 out-migration data from the decennial census as the numerators and state populations by age and sex in 1995 as the denominators. Rates could be broken down by race and ethnicity, if projections of those characteristics were required. These rates form the basis of the projections. They can be used as they are or—as described in the next section—can be adjusted to fit with alternative views of the future.

With or without adjustments, out-migration rates are applied to the launch-year populations of each state, providing projections of out-migrants from all states over the 5-year projection horizon. These numbers are then summed, providing a “pool” of potential in-migrants for each state. This pool is allocated to each state by applying the proportion of all interstate migrants that went to each state during the base period. For example, suppose that a state had 100,000 male in-migrants aged 20–24 between 1995 and 2000 and that nationally there were a total of two million interstate migrants in this age-sex group. Based on this proportion, that state would be projected to receive 5% of the projected pool of male interstate migrants aged 20–24 in each 5-year projection interval. Adjustments to these proportions to account for changing assumptions regarding future migration patterns could also be made, with the constraint that the sum of all state proportions is exactly 100%.

By basing projections of in-migration on the pool of available out-migrants, migrant pool models assure that the total number of interstate in-migrants is exactly equal to the total number of interstate out-migrants. State migration projections are thus consistent with each other and with national projections, in which net internal migration must be zero. This is an important and useful characteristic of migrant pool models.

International migration is generally projected separately from domestic migration in migrant pool models. Special populations such as military personnel and college students are often projected separately as well. We describe approaches to projecting foreign immigration and special populations in Chaps. 7 and 10.

Migrant pool models using the procedures described above can also be developed for counties, but the process is extremely data-intensive, time-consuming, and tedious. In order to project the pool of potential in-migrants, out-migration rates by age and sex (and perhaps by race and ethnicity) would have to be constructed and applied to more than 3,100 counties (or county equivalents) in the United States. A simplified version can be developed, however. Suppose that projections are to be made for all the counties in a particular state. Out-migration rates can be calculated and applied to those counties, providing a projection of the pool of county out-migrants. This pool can be reduced by the number of migrants leaving the state (using historical proportions), leaving a pool of migrants going to other counties within the state. Intrastate migration into each county can then be based on this pool and historical data showing the shares going to each county. Migration from other states can be based on the national number of interstate migrants (excluding those from the state under consideration) and historical data showing the proportions of those migrants going to each county.

6.5.1.2 Multi-Regional Models

The second approach to projecting gross migration uses multi-regional models based on specific place-to-place migration flows (Rogers 1985; Rogers and Woodward 1991; Rogers et al. 2010). In these models, migration is viewed as part of an integrated system of mortality, fertility, and origin-destination-specific population flows by age and sex (and sometimes by other characteristics as well). For example, interstate migration in a multi-regional model could be represented by a 51 $\times$ 51 matrix showing the number of people moving from each state to every other state (including the District of Columbia), by age and sex. Migration rates are calculated by dividing destination-specific gross migration flows by the population of each state of origin, giving each state 50 sets of age-sex-specific out-migration rates, one for each other state in the nation. Because they are based on the population at risk to migration, these rates roughly represent the probabilities of moving from one state to another during a given time period.

Multi-regional models have been used by the Census Bureau in several sets of state population projections (Wetrogan 1988; Campbell 1996). Migration rates in these models were based on data from three different sources. First, the decennial census provided gross migration data by age, sex, and race for a 5-year migration interval. Second, IRS records provided a time series of estimates of annual state-to-state gross migration flows. Third, the CPS provided the data needed to convert 5-year migration rates into 1-year rates. These three sources were combined to create a synthetic time series of annual state-to-state migration flows by age, sex, and race. This data series was used as a basis for projecting future migration flows for each state. As described above for migrant pool models, international migration in multi-regional models is generally handled separately from domestic migration.

6.5.1.3 Two-Region Models

The multi-regional model used by the Census Bureau was extremely data-intensive and required many thousands of calculations. A greatly simplified version can be developed by focusing on two regions, one representing the area to be projected and the other representing the rest of the country. The population of the area to be projected provides the base for calculating out-migration rates, and the population of the rest of the country provides the base for calculating in-migration rates.

Isserman (1993) developed a two-region model for counties in West Virginia. Out-migration rates were calculated for each county by dividing the number of out-migrants by age and sex from 1975 to 1980 by the county's 1975 population for each age-sex cohort. In-migration rates were calculated by dividing the number of in-migrants by the 1975 population of the United States (minus the county's population) by age and sex. These migration rates were calculated in a manner similar to that shown in Table 6.3 for Arizona. Projections of out-migration were made by applying out-migration rates to the county's population, and projections of in-migration were made by applying in-migration rates to the U.S. population (minus the county's population). Foreign immigration was lumped in with domestic in-migration, but no separate projection was made for foreign emigration.

Two-region models retain many of the benefits of full-blown multi-regional models while avoiding much of their cost. We believe they are easier to apply than the simplified version of the migrant pool model described above. An example illustrating the application of a two-region model is given in Chap. 7.

6.5.1.4 Assessment of Gross Migration Models

Gross migration models have several theoretical advantages over net migration models and, in our previous book (Smith et al. 2001, pp. 101–104), were our preferred approach to constructing cohort-component projections for states and counties (but not for subcounty areas). With the ACS replacing the census long form as the major source of detailed migration data, we have revised our opinion on this point. As noted previously, migration data from the ACS have a number of shortcomings compared to migration data from the decennial census. Adjustments to the ACS data can reduce some but not all of these shortcomings. Moreover, ACS migration data are best suited for single-year projection models, which require significantly more resources to implement than 5-year models. Synthetic rates based on a variety of data sources could also be constructed, but such an undertaking would require a substantial investment of resources.

We believe gross migration models can still be usefully employed for state-level projections, especially when ACS data are combined with data from other sources. At this point, however, we believe the scarce resources available for county and subcounty population projections can generally be used more wisely by focusing on net migration models rather than gross migration models. Future research, of course, could cause us to revise our opinion on this point.

6.5.2 Net Migration

6.5.2.1 Top-Down Models

The first approach to projecting net migration focuses on estimates of total net migration rather than separate estimates for each age-sex cohort. It requires two steps. First, projections of total net migration are made, based on recent levels, historical trends, structural models, or some other procedure. Second, these projections are broken down into age-sex categories, based on distributions observed in the past. We call this a "top-down" approach because projections for individual age-sex groups are derived from projections of total net migration. This was the approach taken in the earliest sets of cohort-component projections made for states and regions in the United States (Thompson and Whelpton 1933; U.S. Census Bureau 1957).

The Census Bureau's 1957 state projections provide an illustration of this approach. Three different migration assumptions were made: one based on the continuation of the average annual net migration levels observed for each state between 1950 and 1955, one based on the levels observed between 1940 and 1955, and one based on the levels observed between 1930 and 1955. These projections of total net migration were then broken down into age-sex groups for each state according to the distributions observed during the base period. The three different migration assumptions provided the basis for developing several alternative sets of population projections (U.S. Census Bureau 1957).

This approach has been used for the international migration component in several sets of national population projections in the United States (Day 1992, 1996a, b) and for constructing county projections incorporating updated information on net migration flows (Nakosteen 1989). In addition, several economic models have focused on levels or rates of total net migration, both for analyzing the determinants of migration and for forecasting future net migration flows (Clark and Hunter 1992; Coulombe 2006; Greenwood and Hunt 1989; Murdock et al. 1984).

6.5.2.2 Bottom-Up Models

The second approach to projecting net migration focuses on the development of separate net migration rates for each age-sex cohort in the population (cohorts can also be broken down into racial or ethnic categories). Projections are based on the application of age-sex-specific net migration rates to the base population by age and sex. We call this a "bottom-up" approach because total net migration for an area is the sum of the values projected for each age-sex group.

Most applications of this approach use the population of the area to be projected as the denominator for the net migration rates. For example, projections for the state of Alaska would use the population of Alaska as the denominator for calculating net migration rates. We describe an alternative later in this section. We illustrate the bottom-up approach using state projections published by the Census Bureau in 1983 (U.S. Census Bureau 1983).

Demographers at the Census Bureau used a combination of vital statistics and survival rate techniques to estimate 1970–1980 net migration flows for each state, by age and sex. They adjusted these estimates to account for changes in census undercount between 1970 and 1980, and subtracted changes in the military population to provide net migration estimates for the civilian population. Net migration rates by age and sex were calculated by dividing these civilian net migration estimates by the civilian populations of each state, by age and sex. The denominators used in these rates were the 1970 populations "survived" forward to 1980 using 10-year survival rates by age and sex. Projections for 1990 were made by applying these migration rates to the "survived" 1980 civilian populations of each state. Projections of the military population were added as a final step. The same procedures were repeated to provide projections for 2000.

Net migration models generally combine the effects of international and domestic migration. When net migration is calculated as a residual, this is by far the simplest approach. Separate projections of foreign immigration could be made, however, by subtracting the impact of net foreign immigration from total net migration in the base data, and developing separate assumptions regarding future net flows of foreign and domestic migrants.

One drawback of net migration models is that they create inconsistencies in projections for a group of areas. Consider projections for states, for example. The application of constant net migration rates to states with rapidly growing populations leads to steadily increasing levels of net in-migration over time, but the application of constant rates to states with slowly growing (or declining) populations leads to slowly growing (or declining) levels of net out-migration. This creates an inconsistency because net internal migration for states must sum to zero. It can also lead to bias because projections based on net migration rates tend to be too high for rapidly growing places and too low for slowly growing or declining places (Isserman 1993; Rogers 1990; Smith 1986).

Some of the problems associated with net migration models can be reduced by changing the denominators used in constructing migration rates. Net migration rates for rapidly growing areas can be based on the population of a larger geographic unit rather than of the area itself. For example, rates for rapidly growing states can be based on the national population (minus the state population) rather than the state population. This change has been found to greatly reduce projected rates of increase for rapidly growing states (Smith 1986). Alternatively, projections of net migration (or population) can be constrained or controlled in various ways to prevent unreasonably large increases or declines (Smith and Shahidullah 1995). Chapters 7 and 10 discuss several ways to control population projections for smaller areas to an independent projection of a larger area. We believe net migration models can produce reasonable population projections if proper adjustments are made.

6.5.2.3 Hamilton-Perry Method

The effects of net migration and mortality can be combined to create a simplified version of the cohort-component method (Hamilton and Perry 1962; Smith and Shahidullah 1995; Swanson et al. 2010). In this method, cohort-change ratios (CCR) covering the time interval between the two most recent censuses are calculated for each age-sex cohort in the population. These ratios are the same as the census survival rates discussed in Chap. 4, but the notation is slightly different:

$$ {}_{\mathrm{n}}\mathrm{CCR}_{\mathrm{x,l}} = {}_{\mathrm{n}}\mathrm{P}_{\mathrm{x+y,l}} / {}_{\mathrm{n}}\mathrm{P}_{\mathrm{x,b}} $$

where ${}_nP_{x\ +\ y,\ 1}$ is the population aged $x + y$ to $x + y + n$ in year l; ${}_nP_{x,b}$ is the population age x to $x + n$ in year b; x is the youngest age in an age interval; n is the number of years in an age interval; l is the year of the most recent census; b is the year of the second most recent census (or intercensal population estimate); and y is the number of years between censuses or intercensal estimate and the latest census.

For example, Whitman County, Washington had 2,182 residents aged 35–39 in 2000 and 1,967 residents aged 45–49 in 2010, yielding a cohort-change ratio of:

$$ 0.9015 = 1{,}967/2{,}182 $$

Cohort-change ratios can be calculated for each age-sex group in the population; they can also be calculated for different racial/ethnic groups. Projections can then be made by multiplying these ratios by the launch year population in each age-sex group:

$$ {}_{\mathrm{n}}\mathrm{P}_{\mathrm{x+y,t}} = \left({}_{\mathrm{n}}\mathrm{CCR}_{\mathrm{x,l}}\right) \left({}_{\mathrm{n}}\mathrm{P}_{\mathrm{x,l}}\right) $$

where ${}_nP_{x\ +\ y,t}$ is the population age $x + y$ to $x + y + n$ in year target year t.

To extend our example of Whitman County, the 2010 census counted 2,003 residents aged 35–39. Using the CCR calculated above, we can project the population aged 45–49 in 2020 as:

$$ 1{,}806 = (0.9015)\ (2{,}003) $$

The Hamilton-Perry approach is particularly valuable for census tracts and other small areas in which data on the components of growth are difficult or impossible to obtain. However, it can also be useful in larger areas if certain precautions are taken. We give a complete numerical example and discuss the strengths and weaknesses of this method in Chap. 7.

6.6 Implementing the Migration Component

Migration is difficult to measure or even to define. A number of complex issues must be addressed when collecting data, choosing assumptions, making adjustments, and formulating models. How can the migration component be implemented in a cohort-component projection model?

6.6.1 Choosing Appropriate Models

The first issue that must be confronted is the choice of the projection model. Should the model be based on gross or net migration data? Should it be a structural model or one based on the extrapolation of past trends? If a structural model is used, what explanatory variables should be included? If an extrapolation model is used, on which migration rates should it be based and how should those rates be extrapolated into the future? What demographic characteristics should be included?

The answers to these questions will depend primarily on three factors: the expected use of the projections, the availability of input data, and the amount of time and money available to complete the projections. If the projections will be used to evaluate the demographic effects of different economic scenarios, a structural model is needed. If projections of specific origin-destination migration flows are needed, a multi-regional model must be used. If projections by race and ethnicity are needed, the migration data must include race and ethnicity characteristics. The expected use of the projections is a major determinant of the choice of projection model and the structure of that model.

Equally important is the availability and reliability of input data. As noted previously, gross migration data are often unavailable for small areas. Net migration data, on the other hand, are available or can be developed for virtually any geographic area with data from two consecutive censuses. The same is true for the data required by the Hamilton-Perry method. The availability of reliable input data is a critical factor in the choice of the migration model.

Resource constraints also play a role. Time and money costs increase with the complexity of the method and with the level of geographic and demographic detail required. In many instances, the amount of time and money available to complete a project will have a significant impact on the choice of the projection method.

6.6.2 Choosing Data and Assumptions

Migrant pool, multi-regional, two-region, and net migration models provide an operational framework for calculating and projecting migration rates, but nothing in the models themselves provides any guidance regarding the choice of data or assumptions. Which historical migration rates provide the most realistic foundation upon which to build a set of population projections? Will future rates be higher, lower, or the same as those observed in the recent past? Will migration rates go up for some regions and down for others? Will changes in migration rates be the same for all age, sex, and racial/ethnic groups? There are no simple answers to these questions. The analyst will have to develop assumptions based on personal knowledge of historical migration patterns and expectations regarding future trends. A number of different approaches can be followed in choosing migration rates and projecting them into the future.

The simplest approach (and the most commonly used for small-area projections) is to hold migration rates constant at recent levels. For example, one set of state projections published be the Census Bureau assumed that 1970–1980 net migration rates by age and sex would remain constant over the projection horizon (U.S. Census Bureau 1983). In another set, gross out-migration rates and in-migration proportions observed from 1955 to 1960 were held constant (U. S. Census Bureau 1966).

Migration rates from several different time periods can also be used. The Census Bureau's first published set of state projections were based on the average annual levels of civilian net migration observed during three different historical time periods: 1950–1955, 1940–1955, and 1930–1955. These three migration scenarios were combined with several different fertility assumptions to provide four alternative sets of state projections. These alternative sets were not intended to be used as predictions or forecasts, but simply as illustrative projections of the future population under specific assumptions regarding changes in the components of growth.

Migration rates may not remain constant over time, of course. Does this imply that holding recent rates constant is a poor assumption? No, not necessarily. Will recent rates go up or down? Will they change a lot or only a little? Will the changes be the same or different for various population subgroups? If we cannot answer these questions with some degree of confidence, assuming that a recent set of migration rates will remain unchanged may be the best assumption we can make.

If the analyst chooses to project changes in migration rates over time, what approaches can be followed? One is to assume that a given set of migration rates will gradually converge toward another set over time. For example, the Census Bureau developed a series of state population projections using a migrant pool model in which out-migration rates for each state were projected to converge toward the average of all states over a 50-year period (U.S. Census Bureau 1966). At the same time, it was assumed that in-migration distributions would converge toward each state's population distribution. The result of this approach was that state differences in net migration rates declined over time. This outcome is consistent with economic theories in which migration acts as an "equilibrating mechanism," reducing regional differences in wages and economic opportunities (Hunt 1993; Sjaastad 1962).

Another way to account for changing migration rates is to extrapolate past trends into the future. The Census Bureau followed this approach in several sets of state projections (Campbell 1996). For example, they used IRS migration data from 1975 to 1994 to create a series of 19 annual observations on each of 2,550 state-to-state migration flows (i.e., 51 origin states and 50 destination states). They used these data to produce annual state-to-state migration rates and projected those rates into the future using a time series regression model:

$$_{\mathrm{i,j}}\mathrm{Y}_{\mathrm{t}} = (\mathrm{b})\left(_{\mathrm{i,j}}\mathrm{Y}_{\mathrm{t-1}}\right)$$

where $_{i,j}Y_t$ and $_{i,j}Y_{t-1}$ represent the first differences of the natural logarithms of the migration rates from state i to state j in time periods t and $t-1$, respectively, and b is a coefficient estimated by the regression.

Research conducted at the Census Bureau has shown that projections from time series models become increasingly inaccurate as the projection horizon increases. For horizons of 10 years or longer, extrapolations of average annual values from the base period were found to forecast migration rates more accurately than a time series model (Campbell 1996). Because of these findings, the Census Bureau gradually phased out the time series model as the projection horizon increased. For the first 5 years of the projection horizon, projections were based exclusively on the time series model. For the next 10 years, projections based on the average annual values from the base period were gradually phased in. After 15 years, projections were based exclusively on the average annual values found during the base period. The procedures followed by the Census Bureau illustrate the fact that extrapolating past migration trends can lead to unrealistic projections if carried too far into the future.

Another approach to projecting migration rates is to develop structural models in which migration is tied to projections of other variables. Economic variables are the most commonly used for projection purposes. Structural models provide an alternative to holding recent migration rates constant, extrapolating changes in historical rates, or assuming that rates will gradually converge toward another set of values. They also permit migration trends to be related to various theories of migration or alternative economic scenarios. We discuss structural models in Chap. 9.

6.6.3 Accounting for Unique Events and Special Populations

In addition to deciding which data, assumptions, and techniques to use for a set of population projections, the analyst must decide how to account for unique events and special populations. Unique events are those having a substantial but short-lived impact on an area's migration patterns and are not likely to be repeated. For example, the Mariel boatlift brought more than 125,000 Cuban immigrants to Florida within a 6-month period in 1980, a volume of foreign immigration seen neither before nor since. Most of these immigrants settled in south Florida, making their impact on the local area much greater than their impact on the state as a whole. Natural disasters can also have an impact. Swanson et al. (2009) estimated that Hurricane Katrina reduced the 2010 populations of 79 ZIP code areas in Louisiana and Mississippi by 311,150 people (21.2%) compared to what they would have been had the hurricane not struck. Adjustments for these and similar events are somewhat subjective, but must be made to avoid projecting events that are not likely to be repeated.

Unique events often involve changes in special populations. Special populations are groups of people who are in an area because of an administrative or legislative action (Pittenger 1976). Examples include college students, prison inmates, military personnel, and residents of nursing homes. Special populations are affected by a different set of causal factors than the rest of the population; consequently, changes in special populations are generally unrelated to changes in the rest of the population. If changes in special populations are substantial, it is important to account for them separately when implementing the cohort-component method. We discuss this issue more fully in Chap. 10.

Accounting for unique events and special populations is especially important at the county and subcounty levels because their impact is often highly localized, affecting a few areas dramatically while leaving other areas largely unaffected. Examples include the opening or closing of a military base, prison, or state mental hospital; the development of a large housing project; the construction of a new road or transportation system; and the growth or decline of a major employer. Events like these can have a huge one-time impact on migration flows. If migration rates are not adjusted, the analyst in essence will be projecting that these events will be repeated in every future projection interval.

6.6.4 Accounting for Data Problems

As we have noted, migration data from the ACS differ in several important ways from the migration data collected on the long form of the decennial census. Particularly problematic for population projections is the smaller sample size and 1-year migration interval. Furthermore, less detail on the demographic characteristics of migrants will be released by the Census Bureau than was the case for recent decennial censuses. As has been true in previous censuses, no out-migration data are available for most subcounty areas.

How can these and other data problems be handled? First, it is essential to study the migration data carefully, looking for anomalies and inconsistencies among different age, sex, and racial/ethnic groups. This is necessary for both gross and net migration data and is especially important for small areas and when unusual events occurred during the reference period. When anomalies or inconsistencies are found, adjustments to the migration data must be made or synthetic rates must be developed. Adjustments can be made using the procedures described earlier in this chapter. Synthetic rates for specific population subgroups can be based on data from an adjacent age group, a corresponding sex or racial group, a similar county, a larger geographic area, or a model migration schedule (Pittenger 1976; Rogers et al. 2010). Making adjustments and developing synthetic rates is a time-consuming and somewhat subjective process, but we believe it generally leads to better projections than could be made by slavishly adhering to an official but dubious migration data set.

6.6.5 Converting Data to Other Time Intervals

The ACS is currently the only source of detailed gross migration data for all areas in the United States. It provides data for 1-year migration intervals, whereas gross migration data from previous censuses covered 5-year intervals. Net migration estimates can be constructed for a variety of migration intervals, but are most reliable for 10-year intervals based on data from two consecutive decennial censuses or 5-year intervals where quinquennial censuses are conducted (e.g. Australia, Canada, New Zealand). Can migration data based on one interval be converted into intervals of different lengths?

Conversions of net migration data can be made easily, at least for estimates of total net migration. For example, 10-year estimates can be converted into 5-year estimates simply by dividing by two. Because net migration data are measured as residuals rather than actual events, the conversion process does not change the interpretation of the data: Regardless of the interval covered, the data reflect the net population change due to migration. However, such conversions mask temporal variability within the net migration interval and will not be very accurate if migration trends have changed substantially.

For example, net migration for San Diego County was estimated as 15,582 between 2000 and 2010, yielding a 5-year estimate of 7,791 for each half decade (State of California 2011). Estimates based on annual birth, death, and population data, however, indicated that net migration was 16,011 between 2000 and 2005 and −429 between 2005 and 2010. Dividing the 10-year estimate by two provided an average of the two 5-year periods, but missed the impact of the severe economic recession that reduced population growth dramatically in the latter part of the decade. When net migration has been changing fairly rapidly over time, it will generally be better to create new net migration estimates than to convert existing estimates into intervals of a different length.

Converting age-specific net migration data to other time intervals is substantially more complicated than converting estimates of total net migration. Consider net migration from 2000 to 2010, for example. Persons aged 10–14 in 2000 were 15–19 in 2005 and 20–24 in 2010. This cohort thus passed through two different 5-year age groups during the decade. Which one should be used for calculating 5-year net migration estimates for a 5-year age group? A common solution is to calculate the 10-year net migration flow for each age cohort, divide by two, and take an average of two adjacent cohorts (Irwin 1977). In the example mentioned above, one would use 10-year net migration estimates for persons aged 5–9 and 10–14 in 2000, divide each by two, and take an average to obtain an estimate of 5-year net migration for persons aged 10–14 in 2000. Although this "adjacent cohort" procedure works fairly well if net migration rates do not vary too much from one age group to another, it can lead to large errors in instances where there are large differences in rates between adjacent cohorts (Irwin 1977).

For gross migration, the impact of multiple moves and deaths of migrants makes it very difficult to convert data from one length of interval to another. For example, 5-year migration numbers cannot be calculated simply by multiplying 1-year numbers by five. Studies of this relationship have found that multiplying 1-year migration rates by five greatly overstates the actual 5-year migration rate (Ihrke and Faber 2012; Rees 1977; Rogerson 1990). Although some research on converting 1- and 5-year data to different intervals has been done, the conversion factors have been found to vary from place to place and change over time (Long and Bortlein 1990; Rogers et al. 2003). These studies focused primarily on total migration flows; the conversion process would be much more complicated if migration were divided into demographic subgroups (e.g., age and sex).

Because of these problems, it is risky to convert migration data for one interval into data for an interval of a different length (especially for gross migration). In most circumstances, we believe it is better to use projection intervals that are consistent with the length of the migration interval rather than trying to convert data from one interval to another. That is, it is better to use 1-year projection intervals when using 1-year migration data, 5-year intervals when using 5-year migration data, and 10-year intervals when using 10-year migration data. If projections for intervening target years are needed, they can be constructed using interpolation procedures (see Chap. 10 for details). However, as noted below, combining data from several different sources may facilitate the conversion of data from on length of interval to another.

6.7 Conclusions

Migration has not received nearly as much attention from population researchers as fertility and mortality, perhaps because of the lack of comprehensive data and difficulties in developing clear definitions and adequate measures (Edmonston and Michalowski 2004; Greenwood 1997; Morrison et al. 2004; Rogers et al. 2010). Yet, migration is an important component of change affecting the size, composition, and geographic distribution of the U.S. population. It is often the most volatile component of population growth for states and local areas, both in terms of changes over time and place-to-place differences for a given period of time. It is frequently the major determinant of state and local population growth as well (Smith and Ahmed 1990).

State and local migration is affected by factors that can change dramatically within a short time. In San Bernardino County, California, for example, annual net migration declined from 7,548 in 2006 to −17,214 in 2008 (State of California 2011). The fundamental reason for dramatic changes like this is that migration is considerably more susceptible than either fertility or mortality to changes in economic conditions, employment opportunities, housing patterns, transportation conditions, and neighborhood characteristics. This volatility makes migration rates more difficult to forecast accurately than either mortality or fertility rates (Irwin 1977; Kulkarni and Pol 1994; Nakosteen 1989; Pittenger 1976). Due to its potential volatility and its impact on total population growth, migration contributes more to the uncertainty of cohort-component projections for states and local areas than do either mortality or fertility. In general, the smaller the geographic region, the greater the difficulty of developing accurate migration forecasts.

Migration not only affects the total population of an area, but its age, sex, race, ethnicity, income, education, and other characteristics as well. In California, for example, non-Hispanic whites accounted for nearly 80% of the population in 1970 but only 40% in 2010. This rapid decline was caused primarily by foreign immigration. In Sumter County, Florida, the population aged 65 and older rose from 13.1% of the total population in 1970 to 43.4% in 2010; this increase was caused by primarily by the huge number of retirees moving into the county. The impact of migration on the demographic characteristics of states and local areas can scarcely be overstated.

We believe there are a number of research opportunities that may lead to better migration projections. One is the development of synthetic migration rates based on a combination of data sources and methods. The Census Bureau used this approach in several sets of state population projections, drawing on data from the IRS, the CPS, and the long form of the decennial census (Wetrogan 1988; Campbell 1996). Rogers and colleagues used this approach to develop model migration rates based on regularities in migration patterns (Rogers and Castro 1984; Rogers et al. 2010). Smith and Rayer (2013) combined data from the IRS, CPS, and the ACS to construct migration projections for the state of Florida. Synthetic migration rates for specific demographic subgroups could also be developed, using data from adjacent age groups, corresponding sex or racial groups, similar geographic areas, or model migration schedules.

The use of multiple data sources and methods might be particularly useful for converting migration data to intervals of differing lengths (e.g., 1- to 5-year). Although research on this topic has not been particularly successful to date, systematic relationships may be discovered that will permit useful conversions, at least under some circumstances. If 1-year migration data could be converted into 5-year data, 5-year age groups and 5-year migration intervals could be used in the construction of cohort-component population projections, most likely reducing the degree of variability inherent in those projections.

We also believe research into time series methods, such as ARIMA models, may yield useful techniques for forecasting migration. Most of the research on time series forecasting models has focused on international migration at the national level (Bijak 2011; de Beer 1997; Hyndman and Booth 2008; Wilson and Bell 2004). We are aware of only two studies that have applied these methods for subnational forecasting. Lee et al. (2002) used a first order autoregressive model for forecasting domestic and international migration to California and Campbell (1996) use a lagged dependent variable model to forecast state-to-state domestic migration flows. Time series migration models appear to perform best for short-range forecasts (Campbell 1996; Land 1986) and might be particularly useful during transition periods away from abnormally high or low migration levels. We believe that creativity in the use of data sources and the application of disparate methods may lead to substantial improvements in migration data sets and methodologies, with beneficial implications for the production of population projections.

One potential threat regarding migration data sources must be mentioned. Concerns about state and federal budget deficits may lead to cuts in funding for a wide variety of government programs, including the ACS. If this were to happen, the only source of detailed gross migration data would become less reliable or even disappear, severely limiting the use of gross migration models for the construction of cohort-component population projections.

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Chapter 7
Implementing the Cohort-Component Method

We have now discussed mortality, fertility, and migration—the three components of population change. In this chapter, we describe how to put these components together in a complete projection model. We begin with a discussion of several issues that must be considered when setting up a cohort-component model. Then, we present three step-by-step examples, each based on commonly used computational procedures. These examples illustrate three different approaches to projecting migration, the most difficult component of population growth to forecast accurately for states and local areas. We close with an assessment of the strengths and weaknesses of the cohort-component method.

Our strategy in this chapter is to describe the simplest, most straightforward applications of the cohort-component method. In Chap. 10, we discuss several additional factors that must be considered in some circumstances: adjusting for special populations, controlling to independent population or migration totals, and developing temporal or age-group interpolations.

7.1 General Considerations

To preserve the integrity of age cohorts as they progress through time, it is helpful to follow two basic principles: (1) The number of years in the projection interval should be greater than or equal to the number of years in the cohort, and (2) If the number of years in the projection interval is greater than the number of years in the cohort, it should be exactly divisible by the number of years in the cohort. For example, 5-year cohorts are well suited for making projections in 5- or 10-year intervals, but are not well suited for making projections in 1-year intervals. The logic is simple: people aged 10–14 in 2015 will be 15–19 in 2020 (unless they die), but there is no way to know exactly how many will be 11–15 in 2016. Models that stray from these principles can be constructed, but are more complicated and less precise.

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In the past, cohort-component models were often constructed using 5-year age groups and 5-year projection intervals. 5-year intervals were consistent with the most comprehensive source of detailed migration data—the 5-year mobility question asked on the long form of the decennial census—and 5-year age groups satisfied the needs of a wide range of data users. Chapter 6 describes several cohort-component models in which projections were based on 5-year intervals and 5-year age groups.

Starting in 2010, the decennial census no longer collects mobility data. Those data are now collected in the American Community Survey (ACS), but the mobility question refers to place of residence 1 year ago rather than 5 years ago. As a result, the migration data are consistent with 1-year projection intervals and single years of age but not with 5-year intervals and 5-year age groups.

Single-year cohort-component models can also be constructed and are likely to become more widely used as the ACS replaces the decennial census as the primary source of detailed migration data. Single-year models pick up subtleties missed by 5-year models, make it easy to calculate customized age groups (e.g., 5–17), and provide a more detailed picture of changes in the age structure over time. However, they are considerably more time-consuming and costly to construct and maintain than 5-year models. For example, a single-year model with 100+ as the terminal age group has 202 age-sex categories. In contrast, a 5-year model with 85+ as the terminal age category has only 36 age-sex categories. For a 30-year projection horizon, a single-year net migration model requires 202 separate birth, death, and migration rates for each of 30 distinct time periods (18,180 rates). A 5-year net migration model requires only 36 birth, death, and migration rates for six time periods (648 rates). Data management and quality control issues for single-year models become even more imposing when racial/ethnic groups are added to the projections.

In some circumstances, migration data are available only in 10-year intervals (e.g., net migration between two decennial censuses). A common practice is to transform 10-year net migration rates into 5-year rates by dividing by 2 and averaging two adjacent age cohorts (Irwin 1977). Pittenger (1976, p. 26) suggests a similar approach, using geometric interpolation to create 5-year migration rates. Both approaches are acceptable when net migration is relatively stable over the course of the decade but—as noted in Chap. 6—can create problems when it changes substantially. We prefer using 10-year migration rates and 10-year projection intervals in these circumstances.

Models that use 1-year intervals and single years of age provide the most detail—annual projections for individual ages—but require the most data and computations. Models using 5- or 10-year intervals and age groups require less data and computations, but provide less detail. Because more data and computational requirements imply higher costs, a trade-off must be made between level of detail and costs of production. The optimal choice for any particular application will depend on the amount of time and money available, the availability of reliable data, and the purposes for which the projections are used. We discuss these issues more fully in Chap. 12.

Cohort-component models are almost always stratified by age and sex; they are often stratified by race and ethnicity as well. Racial categories can be very basic (e.g., white and nonwhite) or more detailed (e.g., white; black; Asian; Native Hawaiian or Pacific Islander; American Indian or Alaska Native). The most commonly used ethnic categories in the United States are Hispanic and non-Hispanic; for example, recent national projections from the Census Bureau were stratified both by race and by Hispanic origin (U.S. Census Bureau 2012). Less frequently, projections are stratified by household relationship and marital status, often in conjunction with projections of households (Day 1996; Zeng et al. 2006). Raising the level of stratification allows the analyst to take explicit account of the differences in mortality, fertility, and migration rates found among different demographic subgroups. It is obvious—but worth repeating—that additional stratification adds to the costs and complexities of model implementation and maintenance.

Typically, each demographic subgroup in a cohort-component model is projected separately (e.g., white females, white males, nonwhite females, and nonwhite males). These projections are then combined to create projections of other population groups. For example, projections of males and females are summed to provide projections of the total population and projections of white males and white females are summed to provide projections of the white population. The female population is typically projected first because projections of females are needed to develop projections of births. The procedures for applying those rates are the same for each demographic subgroup.

Data availability is a major issue in the construction of cohort-component projections. Net migration estimates can be made for any area in which birth, death, and population data are available for at least two points in time. Gross migration data, however, are much less readily available and simply do not exist for many geographic areas. In many instances, data availability plays an important role in the choice of the projection model.

A final consideration before implementing the cohort-component method is the impact of data error and data consistency. Data problems tend to increase as the level of demographic detail increases and as population size declines. It is important to verify historical population data and, if necessary, adjust the base data or develop an alternative set of rates before running the projection model. Techniques for adjusting and smoothing base data and developing model migration rates are described in Chap. 6, Judson and Popoff (2004), and Rogers et al. (2010).

The cohort-component method requires that assumptions be made regarding future mortality, fertility, and migration rates. The factors influencing these rates and techniques for projecting future rates are discussed in Chaps. 4, 5 and 6. The following examples focus primarily on the mechanics of applying the cohort-component method, but the reader is reminded that the quality of the data and the validity of the underlying assumptions are at least as important as the projection methods themselves.

7.2 Applying the Cohort-Component Method

We describe three applications of the cohort-component method, one based on a gross migration model, the second on a net migration model, and the third on the Hamilton-Perry method. We refer to these as Models I, II, and III, respectively. Models I and II have many similarities, but differ with respect to age detail, projection intervals, and approaches to projecting migration. Model I is based on single years of age and uses 1-year gross domestic migration rates. Model II is based on 5-year age groups and uses 5-year net migration rates. Model III combines the mortality and migration components by using 10-year cohort-change ratios and applies a different technique for projecting fertility than Models I and II.

Applications of the first two models involve four basic modules or steps, computed in the following sequence: mortality (or survival), migration, fertility, and the final projection. In the third model (Hamilton-Perry), the first two modules are combined. Figure 7.1 provides an overview of these four modules for Model I, the most complex of the three models.

We apply all models using data for females in Maricopa County, Arizona and develop projections from 2010 to 2040. We provide details on the computations only for the first target year for each model (2011 for Model I, 2015 for Model II, and 2020 for Model III); computations for the other target years follow the same procedures. In all models, age refers to a cohort's age at last birthday.

Few off-the-shelf software packages are available for constructing cohort-component population projections; consequently, the analyst will generally have to develop a customized computer program. If small numbers of projections are to be made, they can be implemented fairly easily using an electronic spreadsheet. If large numbers are needed, spreadsheets become cumbersome. In these instances it is easier to construct projections using SAS, SPSS, or a similar statistical package, or by using a formal programming language such as Java or C++. Relational database systems (e.g., Oracle, MySQL, SQL Server, and DB2) are useful for data documentation, storage, retrieval, and management. Software issues are discussed more fully in Chap. 14.

7.2.1 *Gross Migration (Model I)*

International migrants often have different characteristics than domestic migrants and are influenced by different motivating factors. Consequently, if international immigration is an important component of growth for a particular state or local area, it is useful to project it separately from domestic migration. In our first example, we draw such a distinction. Using 2010 as a launch year and 2011 as a

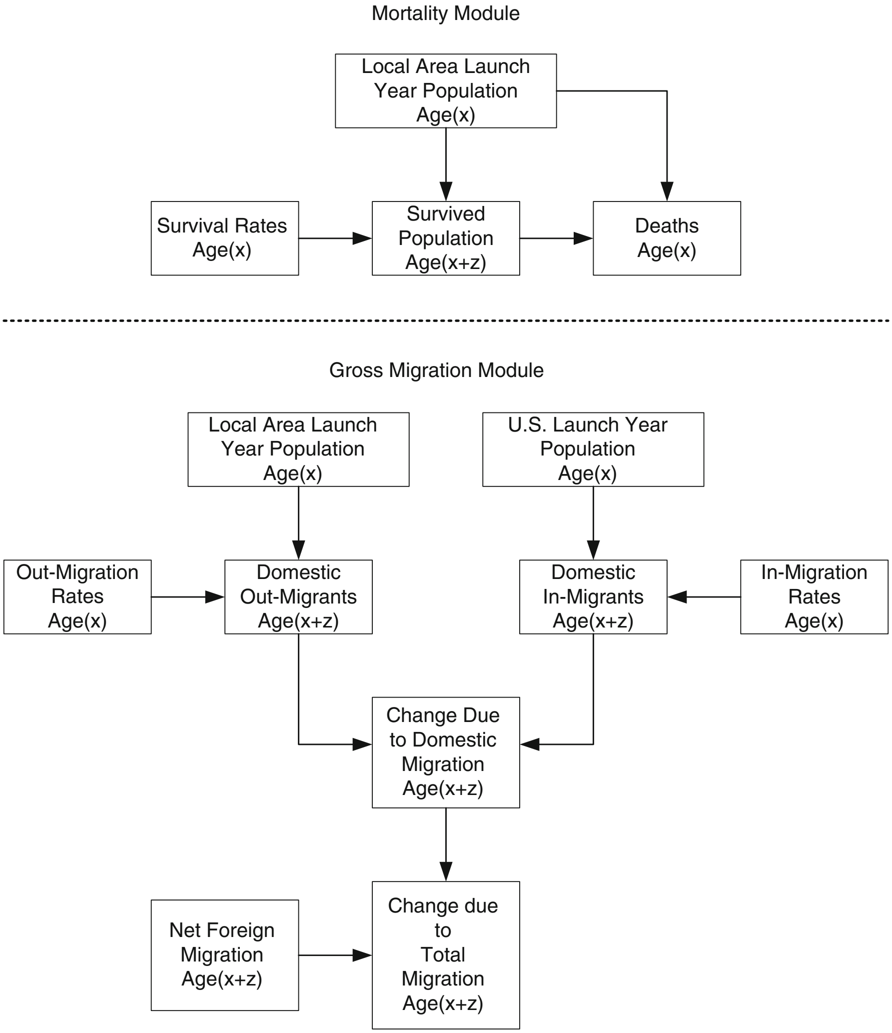

Fig. 7.1 The complete cohort-component model (Model I)

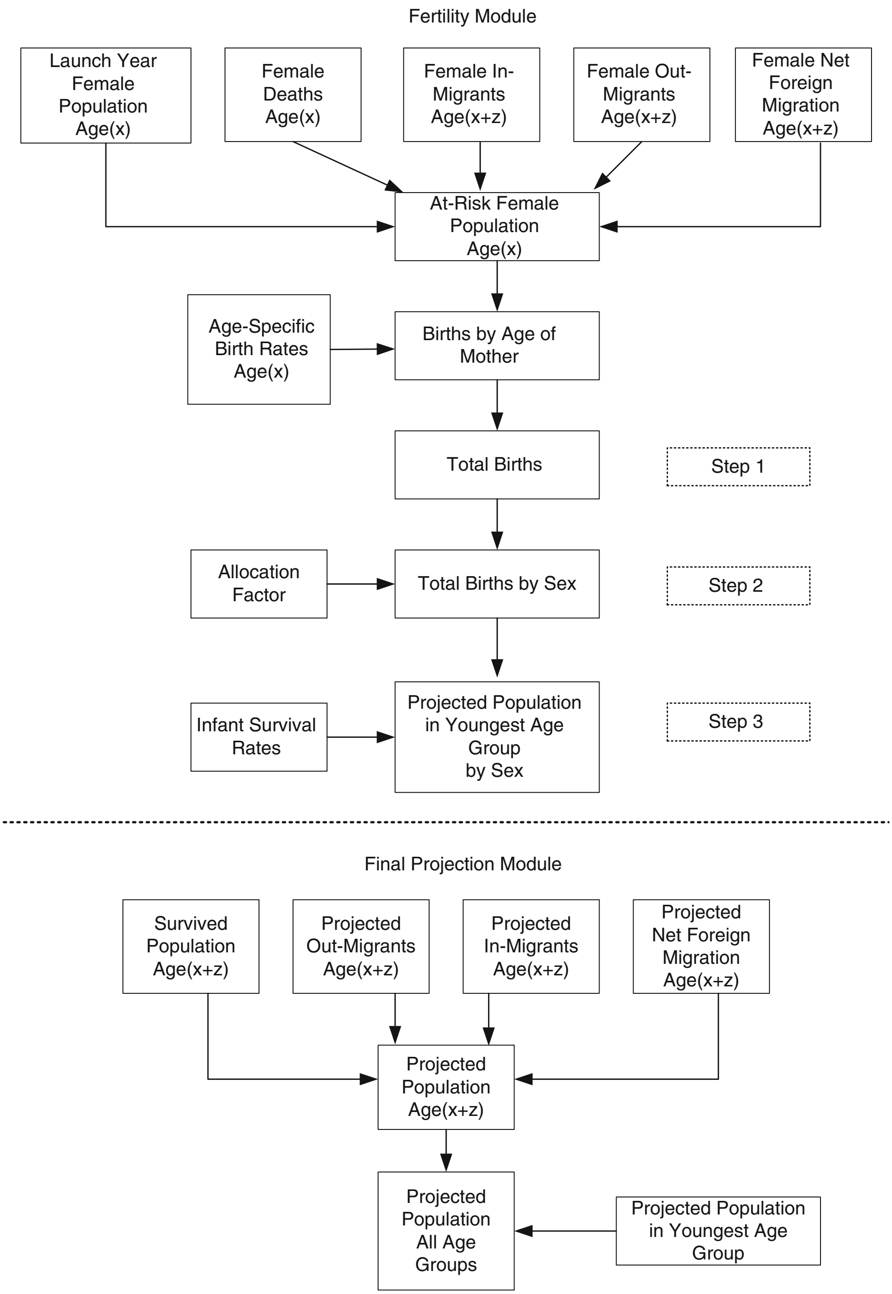

Fig. 7.1 (continued)

target year, we develop a 1-year, two-region gross migration model for females in Maricopa County, Arizona. The data required for this projection include:

1. 2010 female population by age,
2. Age-specific birth rates and the distribution of births by sex,
3. Age-specific survival rates for females,
4. Age-specific domestic in- and out-migration rates for females, and
5. Age-specific net international migration estimates for females.

The 2010 population data came from the decennial census. Age-specific birth rates were calculated using 2010 birth and population data and the procedures described in Chap. 5. Age-specific survival rates were based on Arizona life tables for 2010, using the procedures described in Chap. 4. Domestic in- and out-migration rates were based on 2007–2008 gross migration data for Maricopa County—as reported in the ACS and national PUMS files—and 2007 population estimates for Maricopa County and the United States. The procedures for calculating migration rates are described in Chap. 6. The data and assumptions used to project net international migration are discussed later in this chapter.

7.2.1.1 Mortality Module

The first step in the projection process is to calculate the number of people in the launch year (2010) who will survive to the target year (2011). This can be done by multiplying the launch year population by the survival rate for each age group:

$$_{\mathrm{n}}\mathrm{SURVP}_{\mathrm{x+z,t}} = \left(_{\mathrm{n}}\mathrm{P}_{\mathrm{x,l}}\right)\left(_{n}\mathrm{S}_{x}\right)$$

where x is the youngest age in the age group; n is the number of years in the age group; z is the interval between the launch and target years; t is the target year; l is the launch year; *SURVP* is the survived population; P is the population; and S is the probability of surviving for z more years. In this example, l is 2010, t is 2011, and z is 1 year.

Table 7.1 shows the application of survival rates for selected age groups. For example, the survived population aged 5 in 2011 equals the population aged 4 in 2010 multiplied by its survival rate (i.e., the probability that a person aged 4 lives one more year):

$$(27{,}881)\ (0.99982) = 27{,}876$$

If needed, deaths over the projection interval for a particular age group can be calculated by subtracting the survived population aged $x + z$ from the launch year population aged x:

$$_{\mathrm{n}}\mathrm{D}_{\mathrm{x,l\ to\ t}} = {_{\mathrm{n}}\mathrm{P}_{\mathrm{x,l}}} - {_{\mathrm{n}}\mathrm{SURVP}_{\mathrm{x+z,t}}}$$

Table 7.1 Survived female population, Maricopa County, 2011 (Model I)

2010 Age	2011 Age	2010 Population	One-year survival rate	2011 Survived population[a]	2010–2011 Deaths[b,c]
0	1	26,625	0.99495	26,491	134
1	2	27,157	0.99919	27,135	22
2	3	28,364	0.99960	28,353	11
3	4	28,475	0.99975	28,468	7
4	5	27,881	0.99982	27,876	5
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
40	41	28,160	0.99883	28,127	33
41	42	25,586	0.99868	25,552	34
42	43	25,229	0.99857	25,193	36
43	44	24,509	0.99845	24,471	38
44	45	24,751	0.99834	24,710	41
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
80	81	8,499	0.96598	8,210	289
81	82	7,798	0.95973	7,484	314
82	83	7,455	0.95610	7,128	327
83	84	6,940	0.95320	6,615	325
84+	85+	44,695	0.88963	39,762	4,933
Total		1,928,652		1,916,977	11,675

[a]2010 population × survival rate
[b]2010 population − 2011 survived population
[c]Does not include deaths to females born between 2010 and 2011

For example, we can calculate the number of deaths to females aged 4 in 2010 as:

$$27,881 - 27,876 = 5$$

It should be noted that this projection does not refer to the number of deaths actually occurring in Maricopa County between 2010 and 2011. Rather, it refers to the number of deaths occurring to people who were living in Maricopa County in 2010. Although these two numbers will generally be very close (especially in single-year models), they may not be identical because of the effects of migration on deaths occurring within the county.

The computation for the oldest age group is slightly different from the computations for the younger age groups. The survival rate for the oldest age group in the target year is applied to the sum of the populations in the two oldest age groups in the launch year. For example, if the oldest age group in the target year is 85+, the survival rate is applied to the population aged 84+ in the launch year.

In a 1-year model, the survival routine starts with the launch-year population aged 0 (that is, less than age 1) to obtain the survived population aged 1 in the target year. The projected population aged 0 in the target year is based on the number of births occurring between the launch year and target year, as described in the fertility module. In the present example, life expectancy at birth was projected to increase from 82.6 in 2010 to 85.6 in 2040; this increase is consistent with trends projected for the United States (Social Security Administration 2011).

7.2.1.2 Domestic Migration Module

The next step is to project domestic in- and out-migration by applying domestic migration rates to the appropriate at-risk populations. For in-migration, the at-risk population is the U.S. population minus the Maricopa County population; we call this the "adjusted U.S. population." For out-migration, the at-risk population is the Maricopa County population. There are two main approaches to developing migration projections in this manner. The first uses migration rates applied to the launch-year population "survived" to the end of the projection interval and the second uses migration rates applied to the launch-year population. Either approach is acceptable as long as it is applied consistently. We use the first approach in this example because it is somewhat simpler to apply and leads to about the same results.

We project domestic migration in two steps. For in-migration, we multiply projected in-migration rates by the adjusted U.S. population in the launch year. For out-migration, we multiply projected out-migration rates by the Maricopa County population, also in the launch year. The equations for projecting domestic in- and out- migration are:

$$
\begin{gathered}
{}_{n}\mathrm{AUSP}_{x,l} = {}_{n}\mathrm{USP}_{x,l} - {}_{n}\mathrm{P}_{x,l} \\
{}_{n}\mathrm{INMIG}_{x+z,l\ \mathrm{to}\ t} = \left({}_{n}\mathrm{AUSP}_{x,l}\right)\left({}_{n}\mathrm{INMIGRATE}_{x}\right) \\
{}_{n}\mathrm{OUTMIG}_{x+z,l\ \mathrm{to}\ t} = \left({}_{n}\mathrm{P}_{x,l}\right)\left({}_{n}\mathrm{OUTMIGRATE}_{x}\right)
\end{gathered}
$$

where *AUSP* is the adjusted U.S. population; *USP* is the U.S. population; *P* is the population of the area to be projected; *INMIG* is the projection of domestic in-migration; *INMIGRATE* is the *z*-year domestic in-migration rate; *OUTMIG* is the projection of domestic out-migration; and *OUTMIGRATE* is the *z*-year domestic out-migration rate. As always, *x* is the youngest age in the age group; *n* is the number of years in the age group; *t* is the target year; *l* is the launch year; and *z* is the interval between the launch and target years.

As noted in Chap. 6, migration rates can be projected in a number of ways. In this example, we hold them constant over the projection horizon. Table 7.2 shows the domestic migration projections for 2010–2011 for selected age groups. As we did with the survival rate computations, we combine the launch year populations of the two oldest age groups before applying the migration rates for the oldest group. Also, there is no domestic migration projection for the population aged 0 in 2011. Those children were not yet born in 2010 and are accounted for in the fertility module.

As an illustration, consider the migration of females aged 42 in 2010. We compute the number of in-migrants over the projection interval by multiplying

Table 7.2 Projected domestic and international female migration, Maricopa County, 2010–2011 (Model I)

		2010 Population		Migration rate		2010–2011				
						Domestic migration			Net intl. migration	
2010 Age	2011 Age	Maricopa	Adj. U.S.[a]	In	Out	In[b]	Out[c]	Net	Allocation share	Net[d]
									4,576[e]	
0	1	26,625	2,056,120	0.000625	0.042717	1,285	1,137	148	0.01971	90
1	2	27,157	2,044,650	0.000630	0.042931	1,288	1,166	122	0.01971	90
2	3	28,364	2,033,087	0.000638	0.043399	1,297	1,231	66	0.01971	90
3	4	28,475	2,025,519	0.000645	0.043837	1,306	1,248	58	0.01971	90
4	5	27,881	2,022,379	0.000649	0.044078	1,313	1,229	84	0.01674	77
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
40	41	28,160	2,165,542	0.000488	0.030956	1,057	872	185	0.01075	49
41	42	25,586	2,067,442	0.000471	0.030407	974	778	196	0.01097	50
42	43	25,229	2,022,366	0.000458	0.029958	926	756	170	0.01022	47
43	44	24,509	2,030,096	0.000447	0.029440	907	722	185	0.00840	38
44	45	24,751	2,086,481	0.000437	0.028867	912	714	198	0.00880	40
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
80	81	8,499	754,933	0.000300	0.012830	226	109	117	0.00075	3
81	82	7,798	709,520	0.000282	0.012665	200	99	101	0.00056	3
82	83	7,455	682,278	0.000262	0.012557	179	94	85	0.00044	2
83	84	6,940	643,430	0.000239	0.012452	154	86	68	0.00015	1
84+	85+	44,695	4,423,975	0.000117	0.006967	518	311	207	0.00194	9
Total		1,928,652	155,550,825			96,240	70,818	25,422	1.00000	4,576

[a]2010 U.S. population − 2010 Maricopa County population
[b]In-migration rate × adjusted U.S. population
[c]Out-migration rate × Maricopa County population
[d]Allocation share × control
[e]Projected U.S. net intl. migration × projected Maricopa County share of U.S. net intl. migration

the 2010 adjusted U.S. population age 42 by the in-migration rate for that age group. Similarly, we compute the number of out-migrants by multiplying the 2010 county population aged 42 by the appropriate out-migration rate. The net change due to domestic migration is simply the difference between the two. As shown in Table 7.2, the specific computations are:

$$\text{Domestic in-migrants} : (0.000458)\,(2{,}022{,}366) = 926$$
$$\text{Domestic out-migrants} : (0.029958)\,(25{,}229) = 756$$
$$\text{Net change due to domestic migration} : 926 - 756 = 170$$

A two-region model is a relatively simple application of a gross migration model. More complex applications might include the calculation of separate in-migration rates for migrants coming from a variety of locations such as nearby counties, other counties within the same state, and places outside the state (Foot and Milne 1989; Kanaroglou et al. 2009; Raymer et al. 2010). One set of state projections produced by the Census Bureau used a 51 by 51 matrix of origin-destination-specific migration rates (Campbell 1996). The procedures used in more complex models are similar to those described here for a two-region model.

7.2.1.3 International Migration Module

The migration rates described above refer solely to domestic migration, or movements to and from other parts of the United States. We must also account for international migration, or movements to and from other countries. There are several ways to do this.

One is to project immigration and emigration separately. The Office of Immigration Statistics (OIS) collects immigration data for the United States and reports it annually for states and Core Based Statistical Areas (CBSAs). The ACS provides data on the number of in-migrants who lived outside the United States 1 year ago; these data are available for counties and subcounty areas as well as for states and metropolitan areas. Either of these sources can be used as a basis for projections of immigration. Projections of emigration can be based on previous estimates, such as those produced by Martin and Midgley (1999). For example, Smith and Rayer (2013) projected foreign immigration into Florida using PUMS files from the 2005–2009 ACS and projected emigration by assuming that it would equal 22.5% of projected immigration.

Given the lack of comprehensive and reliable emigration data—especially for counties and subcounty areas—projections of international migration are generally based on a net migration approach. The Census Bureau develops annual estimates of net domestic and net international migration for every county in the United States (U.S. Census Bureau 2011a). Some state demographic agencies develop similar estimates for counties in their respective states. Net international migration can be projected by holding recent levels constant, extrapolating previous trends, or making adjustments based on alternative views of the future.

Projections of net international migration can also be made using shares rather than levels (Center for the Continuing Study of the California Economy 2010; San Diego Association of Governments 2010). For example, the Census Bureau estimated that net international migration for the United States was 894,300 between July, 2010 and July, 2011, with 15,500 occurring in Maricopa County (U.S. Census Bureau 2011a). The county's share of the national total can be calculated as:

$$15,500/894,300 = 0.0173$$

Net international migration for Maricopa County can then be projected by applying this share to national projections of net international migration. This is the approach we used to construct the projections shown in Table 7.2. We held the 2010 share constant over the projection horizon and applied it to net international migration projections for the United States (U.S. Census Bureau 2009). Alternatively, we could have extrapolated historical trends in Maricopa County's share of the national total or used expert judgment to adjust its future share.

The ACS collects data on the year in which foreign-born persons came to live in the United States. These data can also be used to project net international migration. For example, 13.9 million foreign-born persons in the 2010 ACS reported that they had entered the United States between 2000 and 2009. Of these, 187,496 were living in Maricopa County in 2010. The county's share of the nation's net international migration over this period can be calculated as:

$$187,496/13,863,080 = 0.0135$$

This estimate is similar to the one calculated above; it could also be used for projecting net international migration in Maricopa County.

The methods described above focus on migration totals. How can the demographic characteristics of international migrants be projected? The simplest approach is to assume that the future net international migration flow for a particular area will have the same characteristics as the flow for the nation as a whole. This will be a reasonable assumption if the mix of countries sending migrants to an area is similar to the mix for the United States and if the analyst believes that mix will continue (data on the origins of international migrants for states and CBSAs are available from the OIS). Another approach is to assume that the future net international migration flow for an area will have the same characteristics as the immigrants reported in the ACS or by the OIS. Both approaches are approximations but will provide reasonable projections in most circumstances. In the present example, we used PUMS data from the 2007 to 2010 ACS to project the age distribution of the net international migration flow in Maricopa County, holding that distribution constant over the projection horizon.

7.2.1.4 Fertility Module

The third step is to project the number of births and the net impact of mortality and migration on the youngest age group. This process has three steps. First, we multiply the at-risk female population (by age) by the projected ASBRs and sum the results to obtain a projection of the total number of births (by *at-risk*, we mean females of childbearing age). Second, we allocate births between males and females using historical proportions. Finally, we survive the births to the target year to obtain the projection of the youngest age group. The equations used in making these calculations are:

$$
\begin{gathered}
{}_{n}\mathrm{ATRISKF}_{x,t} = {}_{n}\mathrm{FP}_{x,l} - (0.5)\left({}_{n}\mathrm{FD}_{x,l\ \mathrm{to}\ t}\right) + \\
\left({}_{n}\mathrm{FINMIG}_{x+z,l\ \mathrm{to}\ t}\right) - \left({}_{n}\mathrm{FOUTMIG}_{x+z,l\ \mathrm{to}\ t}\right) \pm \left({}_{n}\mathrm{FINTMIG}_{x+z,l\ \mathrm{to}\ t}\right) \\
{}_{n}\mathrm{B}_{x,l\ \mathrm{to}\ t} = \left({}_{n}\mathrm{ASBR}_{x,t}\right)\left({}_{n}\mathrm{ATRISKF}_{x,t}\right) \\
\mathrm{B}_{l\ \mathrm{to}\ t} = \sum {}_{n}\mathrm{B}_{x,l\ \mathrm{to}\ t}, \text{ where } \sum \text{ is the sum across all age groups} \\
\mathrm{MB}_{l\ \mathrm{to}\ t} = \left(\mathrm{B}_{l\ \mathrm{to}\ t}\right)(\mathrm{PCTM}) \\
\mathrm{FB}_{l\ \mathrm{to}\ t} = \mathrm{B}_{l\ \mathrm{to}\ t} - \mathrm{MB}_{l\ \mathrm{to}\ t} \\
{}_{n}\mathrm{M}_{0,t} = \left(\mathrm{MB}_{l\ \mathrm{to}\ t}\right)\left({}_{n}\mathrm{MS}_{0}\right) \\
{}_{n}\mathrm{F}_{0,t} = \left(\mathrm{FB}_{l\ \mathrm{to}\ t}\right)\left({}_{n}\mathrm{FS}_{0}\right)
\end{gathered}
$$

where *ASBR* is the age-specific birth rate; *ATRISKF* is the at-risk female population; *FP* is the female population; *FD* is female deaths; *FINMIG* is the projection of female domestic in-migrants; *FOUTMIG* is the projection of female domestic out-migrants; *FINTMIG* is the projection of net female international migration; *B* is the projection of total births; *MB* is the projection of male births; *PCTM* is the percentage of births that are male; *FB* is the projection of female births; ${}_nM_{0,t}$ is the male population projection in the youngest age group; ${}_nMS_0$ is the male infant survival rate; ${}_nF_{0,t}$ is the female population projection in the youngest age group; and ${}_nFS_0$ is the female infant survival rate. As always, x is the youngest age in an age group; n is the number of years in the age group; l is the launch year; t is the target year; and z is the interval between the launch and target years.

The equation for the at-risk population requires further elaboration. Some of the original members of each cohort die, others move away, and new members move in. We assume that women who die during the projection interval live through half the interval (e.g., 0.5 years for a 1-year interval). Therefore, the population for each age cohort in the launch year must be reduced by one-half the deaths occurring over the projection interval. We further adjust the at-risk population by adding domestic in-migrants, subtracting domestic out-migrants, and adding or subtracting net international migration. Our final calculation of the at-risk population (ATRISKF), then, is the female population in the launch year, minus one-half the female deaths during the projection interval, plus female domestic in-migrants, minus female domestic out-migrants, plus or minus female net international migration.

The TFR in Maricopa County was estimated as 2.10 in 2010. In the present example, it is projected to increase to 2.15 by 2020 and then to decline gradually to 2.00 by 2040; this decline is consistent with national trends projected by the Social Security Administration (2011). The age pattern of childbearing is held constant over the projection horizon.

Table 7.3 shows the sequence used for projecting male and female births. Column 2 shows the 1-year ASBR for selected age groups in 2011. The at-risk population for each age group (Column 8) is calculated by starting with the 2010 population, subtracting one-half the deaths, adding domestic in-migrants, subtracting domestic out-migrants, and adding or subtracting net international migration. For females aged 40 in 2010, for example, the at-risk population is calculated as:

$$28{,}160 - (0.5)\,(33) + 1{,}057 - 872 + 49 = 28{,}378$$

Births are computed by multiplying the at-risk population in each age group by the birth rate for that age group. For example, births for women aged 40 in 2010 are calculated as:

$$(28{,}378)\,(0.026205) = 744$$

A projection of the total number of births can be obtained by summing the births projected for all ages. In this example, the sum is 56,909 for the 1-year projection interval.

Table 7.3 Projected births and population aged 0, Maricopa County, 2011 (Model I)

2010 Age	ASBR	2010 Population	Deaths	Domestic In-migrants	Domestic Out-migrants	Net intl. migration	At risk population[a]	Births[b]
15	0.007990	26,681	4	1,023	966	79	26,815	214
16	0.021732	26,950	4	1,194	1,109	83	27,116	589
17	0.036277	26,565	6	1,440	1,244	117	26,875	975
18	0.051088	27,239	10	1,747	1,442	130	27,669	1,414
19	0.065632	26,912	10	2,091	1,587	154	27,565	1,809
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
25	0.119458	27,204	14	2,518	1,863	142	27,994	3,344
26	0.120868	26,578	14	2,357	1,747	142	27,323	3,302
27	0.120593	27,800	14	2,255	1,751	134	28,431	3,429
28	0.118909	27,512	14	2,196	1,669	119	28,151	3,347
29	0.115942	27,661	16	2,184	1,622	113	28,328	3,284
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
40	0.026205	28,160	33	1,057	872	49	28,378	744
41	0.019414	25,586	34	974	778	50	25,815	501
42	0.012957	25,229	36	926	756	47	25,428	329
43	0.006611	24,509	38	907	722	38	24,713	163
44	0.000153	24,751	41	912	714	40	24,969	4
Total		792,772	574	52,027	39,330	2,963	807,858	56,909

	Share of Births	2010–2011 Births[c,d]	Survival Rate[e]	Age 0[f]	2010–2011 Infant deaths[g]
Males	0.51	29,024	0.99178	28,785	239
Females	0.49	27,885	0.99439	27,729	156
Total	1.00	56,909		56,514	395

[a]2010 population − (0.5 × deaths) + in-migrants − out-migrants + net international migration
[b]ASBR × at-risk population
[c]Males = total births × 0.51
[d]Females = total births − male births
[e]Probability of surviving from birth to age 1
[f]Births × survival rate
[g]Births − 2011 population age 0

Drawing on our discussion of the mortality module, we note that this is a projection of the number of births between 2010 and 2011 to women living in the county in 2011, *not* the number of births actually occurring in the county between 2010 and 2011. On average, migrants are at risk of giving birth within the county during only half the projection interval. However, our concern is not the number of births occurring within the county itself, but rather the location at the end of the projection interval of children born during the interval. We assume that babies and young children reside with their mothers at the end of the projection interval, regardless of where they were born. As Isserman (1993) noted, this allows births and the migration of infants to be treated in a single step. Domestic in-migrants and non-migrants are included in the population at risk but domestic out-migrants are subtracted. Net international migration is added if it is positive, subtracted if it is negative. This allows the number of births to be based on the county population at the end of the projection interval.

The bottom panel of Table 7.3 shows the calculation of the population aged 0 in 2011. The first step is to divide projected births into males and females, using historical data on the male proportion of total births (0.51). Birth projections for each sex are calculated as:

$$\text{Male births} : (56{,}909)\ (0.51) = 29{,}024$$
$$\text{Female births} : 56{,}909 - 29{,}024 = 27{,}885$$

We then apply survival rates to the birth projections. The survival rates used in Table 7.3 were derived from life tables and refer to the probability of surviving from birth to age 1. We compute the population aged 0 as:

$$\text{Male population} : (29{,}024)\ (0.99178) = 28{,}785$$
$$\text{Female population} : (27{,}885)\ (0.99439) = 27{,}729$$

If desired, infant deaths from 2010 to 2011 can be computed by subtracting the 2011 population aged 0 from the projected births:

$$\text{Male infant deaths} : 29{,}024 - 28{,}785 = 239$$
$$\text{Female infant deaths} : 27{,}885 - 27{,}729 = 156$$

7.2.1.5 Final Projection Module

The final calculations combine the results from the mortality, migration, and fertility modules. The projected population for each age group is calculated as the survived population plus domestic in-migrants, minus domestic out-migrants, plus or minus net international migration:

$$_{n}p_{x+z,t} = {}_{n}SURVP_{x+z,t} + {}_{n}INMIG_{x+z,1\text{ to }t} - {}_{n}OUTMIG_{x+z,1\text{ to }t} \pm {}_{n}FINTMIG_{x+z,1\text{ to }t}$$

Although the notation is somewhat different, this equation is similar to the demographic balancing equation discussed in Chap. 2. The only difference is the absence of births, which are accounted for in the fertility module and provide the basis for the projection of the youngest age group. The final projection (P_t) is the sum of the projections for all the age groups:

$$P_t = \sum {}_{n}p_{x+z,t}$$

Table 7.4 shows the complete projection for selected age groups, including components of change. Migration for the population aged 0 is shown as zero

Table 7.4 Projected female population, Maricopa County, 2011 (Model I)

2010 Age	2011 Age	2010 Population	2011 Survived Population	2010–2011 Deaths	2010–2011 Migration: Domestic in-migrants	Domestic out-migrants	Net intl. migration	2011 population[a]
Births	0	26,625	27,729[b]	156	0	0	0	27,729
0	1	27,157	26,491	134	1,285	1,137	90	26,729
1	2	28,364	27,135	22	1,288	1,166	90	27,347
2	3	28,475	28,353	11	1,297	1,231	90	28,509
3	4	27,881	28,468	7	1,306	1,248	90	28,616
4	5	27,779	27,876	5	1,313	1,229	77	28,037
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
40	41	25,586	28,127	33	1,057	872	49	28,361
41	42	25,229	25,552	34	974	778	50	25,798
42	43	24,509	25,193	36	926	756	47	25,410
43	44	24,751	24,471	38	907	722	38	24,694
44	45	26,690	24,710	41	912	714	40	24,948
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
80	81	7,798	8,210	289	226	109	3	8,330
81	82	7,455	7,484	314	200	99	3	7,588
82	83	6,940	7,128	327	179	94	2	7,215
83	84	6,525	6,615	325	154	86	1	6,684
84+	85+	38,170	39,762	4,933	518	311	9	39,978
Total		1,928,652	1,944,706	11,831	96,240	70,818	4,576	1,974,704

[a]Survived population + domestic in-migrants − domestic out-migrants + net international migration
[b]2010–2011 survived births

because it is captured in the projection of births. Overall, the number of females is projected to grow from 1,928,652 to 1,974,704 between 2010 and 2011, an increase of 46,052.

It is easy to calculate the overall components of change from Table 7.4. Births can be computed by adding deaths of children born between 2010 and 2011 (156) to the survived population aged 0 (27,729), yielding a projection of 27,885 births. This is considerably more than the projection of deaths (11,831), which implies that the total population is projected to experience a natural increase of 16,054. Maricopa County's female population also increases from both domestic and international migration. Domestic in-migrants exceed domestic out-migrants by 25,422 and net international migration adds another 4,576. Natural increase, net domestic migration, and net international migration thus account for 35%, 55%, and 10%, respectively, of the change in Maricopa County's female population between 2010 and 2011.

Again, we emphasize that these projections of births and deaths are approximations for the numbers actually occurring within the county. For most places, differences between projected births and deaths and those occurring within the area will be very small. For places with high rates of domestic or international migration, however, the differences may be substantial.

7.2.2 Net Migration (Model II)

We illustrate Model II using the same data and assumptions used in Model I, with two differences: (1) We use net migration rates instead of gross migration rates, and (2) We use 5-year age groups and 5-year projection intervals instead of single years of age and 1-year intervals. The basic steps in the projection process are the same for both models: surviving the population, projecting migration, projecting fertility, and summing the components.

In this illustration, we used a 5-year migration interval based on data from 2005 to 2010. The 2005 female population in Maricopa County was based on the Census Bureau's intercensal population estimate for that year (U.S. Census Bureau 2011b). The estimate of the 2005 age distribution (in 5-year age groups) was made by averaging the age distributions from the 2000 and 2010 censuses; this is a commonly used procedure (Espenshade and Tayman 1982). For each age group, estimates of net migration from 2005 to 2010 were made using the forward-survival rate method described in Chap. 6. A 5-year migration interval is consistent with the 5-year age groups used in this example; a 10-year interval based on net migration between 2000 and 2010 also could have been used. Net migration estimates developed in this manner capture the effects of both domestic and international migration.

Net migration rates were calculated by dividing the 2005–2010 net migration estimates by the 2005 adjusted U.S. female population by age. Alternatively, we could have calculated net migration rates using Maricopa County's female population by age as denominators; we discuss the impact of following this approach later in this chapter. Chapter 6 discusses several issues regarding the construction and interpretation of net migration rates. To facilitate a comparison of results from Models I and II, the net migration rates were weighted to produce migration flows that were consistent with those coming from the gross migration model.

7.2.2.1 Mortality Module

Model II requires the use of 5-year survival rates. Other than that, the steps in the mortality module are the same for Model II as they were for Model I. Table 7.5 shows the mortality calculations for Model II. Age-specific survival rates were based on the 2010 life table for females in Arizona; they were projected to increase over the projection horizon in a manner similar to that used for Model I.

7.2.2.2 Migration Module

Net migration models require only one set of migration rates. For each age group, we project net migration by multiplying net migration rates by the adjusted U.S. population in the launch year:

Table 7.5 Survived female population, Maricopa County, 2015 (Model II)

2010 Age	2015 Age	2010 Population	Five-year survival rates	2015 Survived population[a]	2010–2015 Deaths[b,c]
0–4	5–9	138,502	0.99876	138,330	172
5–9	10–14	138,369	0.99948	138,297	72
10–14	15–19	135,874	0.99911	135,753	121
15–19	20–24	134,347	0.99830	134,119	228
20–24	25–29	129,341	0.99764	129,036	305
25–29	30–34	136,755	0.99658	136,287	468
30–34	35–39	131,224	0.99556	130,641	583
35–39	40–44	132,870	0.99397	132,069	801
40–44	45–49	128,235	0.98991	126,941	1,294
45–49	50–54	131,780	0.98495	129,797	1,983
50–54	55–59	124,017	0.97924	121,442	2,575
55–59	60–64	109,421	0.97159	106,312	3,109
60–64	65–69	100,312	0.95947	96,246	4,066
65–69	70–74	77,978	0.93919	73,236	4,742
70–74	75–79	58,416	0.90250	52,720	5,696
75–79	80–84	45,824	0.83955	38,472	7,352
80+	85+	75,387	0.60473	45,589	29,798
Total		1,928,652		1,865,287	63,365

[a]2010 population × survival rate
[b]2010 population − 2015 survived population
[c]Does not include deaths to females born between 2010 and 2015

$$_n\mathrm{NETMIG}_{x+z,1\ \mathrm{to}\ t} = \left(_n\mathrm{AUSP}_{x,1}\right)\left(_n\mathrm{NETMIGRATE}_x\right)$$

where *NETMIG* is the net migration projection; *AUSP* is the adjusted U.S. launch year population; *NETMIGRATE* is the *z*-year net migration rate; *x* is the youngest age in an age group; *n* is the number of years in the age group; *l* is the launch year; *t* is the target year; and *z* is the interval between the launch and target years. If the county population had been used as the denominator in constructing the net migration rates, the county population in the launch year would have been used in this equation instead of *AUSP*.

Table 7.6 shows the net migration projections for females in Maricopa County. For females aged 45–49 in 2015, for example, we project net migration by multiplying the adjusted U.S. population aged 40–44 in 2010 by the net migration rate for that age group:

$$(10,371,927)\ (0.001018) = 10,559$$

As we did in Model I, we combine the launch year populations in the two oldest age groups (ages 80–84 and 85+ in a 5-year model) before applying the migration rate for the oldest age group. Also, we do not directly project net migration for the population aged 0–4 in 2015; this age group is accounted for in the fertility module.

Table 7.6 Projected female net migration, Maricopa County, 2010–2015 (Model II)

2010 Age	2015 Age	2010 Adjusted U.S. population[a]	Net migration rate	2010–2015 Net migration[b]
0–4	5–9	10,181,755	0.000840	8,553
5–9	10–14	10,093,478	0.000794	8,014
10–14	15–19	9,838,775	0.001222	12,023
15–19	20–24	10,476,248	0.001454	15,232
20–24	25–29	10,550,611	0.001715	18,094
25–29	30–34	10,408,034	0.001522	15,841
30–34	35–39	9,960,566	0.000952	9,482
35–39	40–44	9,943,041	0.000741	7,368
40–44	45–49	10,371,927	0.001018	10,559
45–49	50–54	11,298,503	0.001099	12,417
50–54	55–59	11,157,986	0.001134	12,653
55–59	60–64	9,957,343	0.001240	12,347
60–64	65–69	8,633,145	0.000937	8,089
65–69	70–74	6,435,764	0.000596	3,836
70–74	75–79	4,952,632	0.000403	1,996
75–79	80–84	4,076,881	0.000150	612
80+	85+	7,214,136	0.000059	426
Total				157,542

[a]2010 U.S. population − 2010 Maricopa County population
[b]Net migration rate × adjusted U.S. population

7.2.2.3 Fertility Module

Several adjustments to the fertility module used in Model I must be made before it can be used in Model II. First, 1-year fertility rates must be multiplied by 5 to reflect 5-year projection intervals. Second, an adjustment must be made to account for the fact that females pass from one age group to another during the projection interval. Because they spend half the interval in one age group and half in the next older group (on average), ASBRs are typically calculated as the average of the rates for those two groups. We call this the *adjusted ASBR* (*ADJASBR*):

$$_{n}\mathrm{ADJASBR}_{x,t} = \left(_{n}\mathrm{ASBR}_{x,t} + {}_{n}\mathrm{ASBR}_{x+5,t}\right)/2$$

This adjustment can have a substantial impact on birth projections, especially when the population is growing (or declining) rapidly or when some age groups are considerably larger than others.

The equation identifying the at-risk female population also changes, with projected net migration replacing separate projections of domestic in-and out-migration and net international migration:

$$_{n}\mathrm{ATRISKF}_{x,t} = {}_{n}\mathrm{FP}_{x,l} - (0.5)\left(_{n}\mathrm{FD}_{x,l\ \mathrm{to}\ t}\right) + {}_{n}\mathrm{FNETMIG}_{x+z,l\ \mathrm{to}\ t}$$

where *ATRISKF* is the at-risk female population; *FP* is the launch year female population; *FD* is female deaths; *FNETMIG* is the projection of female net

Table 7.7 Projected births and population aged 0–4, Maricopa County, 2015 (Model II)

2010 Age	2015 Age	5-Year birth rate Original[a]	5-Year birth rate Adjusted[b]	2010 Population	2010–2015 Deaths	2010–2015 Net migration	At-risk population[c]	Births[d]
10–14	15–19	0.00000	0.10976	135,874	121	12,023	147,837	16,227
15–19	20–24	0.21951	0.37786	134,347	228	15,232	149,465	56,477
20–24	25–29	0.53621	0.56939	129,341	306	18,094	147,282	83,861
25–29	30–34	0.60256	0.54017	136,755	468	15,841	152,362	82,301
30–34	35–39	0.47777	0.35472	131,224	583	9,482	140,415	49,808
35–39	40–44	0.23167	0.14042	132,870	802	7,368	139,837	19,636
40–44	45–49	0.04917	0.02459	128,235	1,293	10,559	138,148	3,397
Total				928,646	3,801	88,599	1,015,346	311,707

	Share of births	2010–2015 Births[e,f]	Survial rate[g]	2015 Population aged 0–4[h]	2010–2015 Infant deaths[i]
Males	0.51	158,971	0.99467	158,124	847
Females	0.49	152,736	0.99728	152,321	415
Total	1.00	311,707		310,445	1,262

[a]One-year ASBR × 5
[b]Average of ASBR for adjacent age groups
[c]2010 population − (0.5 × deaths) + net migration
[d]Adjusted ASBR × at-risk population
[e]Males = total births × 0.51
[f]Females = total births − male births
[g]Probability of surviving from birth to age 2.5
[h]Births × survival rate
[i]Births − 2010 population aged 0–4.

migration; and *n*, *x*, *z*, *l*, and *t* are as defined previously. Births for each age group are projected by multiplying the adjusted ASBR by the at-risk female population:

$$_{n}B_{x,1\ \mathrm{to}\ t} = \left(_{n}\mathrm{ADJASBR}_{x,t}\right)\left(_{n}\mathrm{ATRISKF}_{x,t}\right)$$

Table 7.7 shows the calculation sequence for births and the population aged 0–4. Column 3 shows the projected ASBR for each age group in 2015; these rates are 1-year rates multiplied by 5. Column 4 shows adjusted ASBRs, calculated as the average of two adjacent sets of ASBRs. For example, the adjusted rate for females aged 10–14 in 2010 is the average of the rates for ages 10–14 and 15–19. The rate for females aged 40–44 in 2010 is one-half the rate for females aged 40–44 because the rate for females older than age 44 is assumed to be zero. The life table survival rate for the 0–4 age group refers to a 2.5-year horizon rather than a 5-year horizon because it is assumed that births and deaths occur evenly throughout the 5-year interval: On average, babies born during the interval face a 2.5-year horizon to the end of the interval.

7.2.2.4 Final Projection Module

The final calculations combine the results from the mortality, migration, and fertility modules (see Table 7.8). The basic equation is about the same as in Model I,

Table 7.8 Projected female population, Maricopa County, 2015 (Model II)

Age	2010 Population	2015 Survived population	2010–2015 Deaths	2010–2015 Net migration	2015 Population[a]
0–4	138,502	152,321[b]	415	0	152,321
5–9	138,369	138,330	172	8,553	146,883
10–14	135,874	138,298	71	8,014	146,312
15–19	134,347	135,753	121	12,023	147,776
20–24	129,341	134,119	228	15,232	149,351
25–29	136,755	129,035	306	18,094	147,129
30–34	131,224	136,287	468	15,841	152,128
35–39	132,870	130,641	583	9,482	140,123
40–44	128,235	132,068	802	7,368	139,436
45–49	131,780	126,942	1,293	10,559	137,501
50–54	124,017	129,796	1,984	12,417	142,213
55–59	109,421	121,442	2,575	12,653	134,095
60–64	100,312	106,312	3,109	12,347	118,659
65–69	77,978	96,246	4,066	8,089	104,335
70–74	58,416	73,236	4,742	3,836	77,072
75–79	45,824	52,720	5,696	1,996	54,716
80–84	37,217	38,472	7,352	612	39,084
85+	38,170	45,589	29,798	426	46,015
Total	1,928,652	2,017,607	63,781	157,542	2,175,149

[a]Survived population + net migration
[b]2010–2015 survived births

except that separate terms for domestic in- and out-migration and net international migration have been replaced by a single term for net migration:

$$ {}_{n}p_{x+z,t} = {}_{n}\mathrm{SURVP}_{x+z,t} + {}_{n}\mathrm{NETMIG}_{x+z,1\ \mathrm{to}\ t} $$

The choice of the migration model can have a significant impact on population projections. As shown in Table 7.9, Model I generates a net migration flow of 147,365 between 2010 and 2015 (including both domestic and international migrants), whereas Model II generates a net migration flow of 157,542, a difference of 6.9%. The differences become greater as the projection horizon increases. Between 2035 and 2040, for example, net migration is 49.4% higher in Model II than Model I. Projections from Model II would have been even higher if the Maricopa County rather than the adjusted U.S. population had been used as the denominator for calculating net migration rates.

Total population change is considerably greater for Model II than Model I. Although migration accounts for most of this difference, births and deaths also play a role. Births are higher in Model II than Model I because the number of women of childbearing age is greater. Over the 30-year projection horizon, there are 90,000 more births and 12,600 fewer deaths in Model II than Model I (not shown here). Because of these differences in projected population change, we believe it is helpful to compare cohort-component projections with projections produced by other projection methods. If the differences are substantial, it may be advisable to

Table 7.9 Net migration and population change, Models I and II, Maricopa County 2010–2040

	Net migration			Population change		
	Model II	Model I	Difference[a]	Model II	Model I	Difference[a]
2010–2015	157,542	147,365	10,177	246,494	230,790	15,704
2020–2025	168,415	130,350	38,065	267,861	216,627	51,234
2035–2040	178,414	119,442	58,972	260,227	170,098	90,129
2010–2040	1,013,989	782,309	231,680	1,566,229	1,228,959	337,270

[a]Model II − Model I

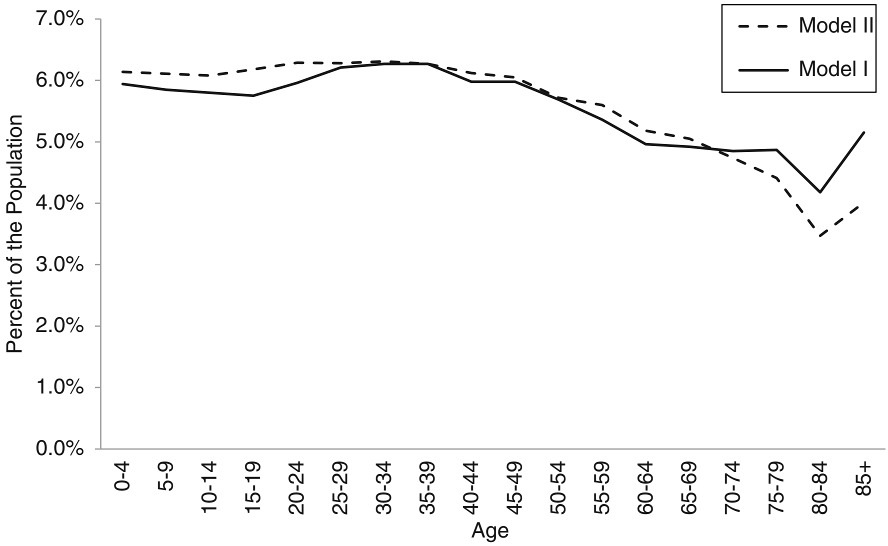

Fig. 7.2 Population distribution by age, Models I and II, Maricopa County, 2040

control the projections of demographic characteristics (e.g., age, sex, race) coming from the cohort-component model to projections of total population coming from other projection methods, especially for net migration models, long projection horizons, and areas that have been growing rapidly. Chapters 8 and 9 describe other projection methods and Chap. 10 discusses several controlling techniques.

The two migration models also lead to differences in the age distribution (see Fig. 7.2). Although the differences are small for most age groups, they are substantially larger at the older ages. These differences highlight the importance of thinking carefully about the implications of the choice of the migration model before making a set of population projections.

7.2.3 Hamilton-Perry (Model III)

Hamilton and Perry (1962) proposed the use of cohort-change ratios as a short-cut way to apply the cohort-component method. The Hamilton-Perry method is similar to a net migration model in which the denominator for migration rates is the population of the area to be projected (in this example, Maricopa County). The major difference is that it treats mortality and migration as a single unit rather than separately. In addition, the fertility component is often simplified by using child-woman ratios rather than ASBRs.

The Hamilton-Perry method projects population by age and sex using cohort-change ratios (CCR) based on data from two consecutive censuses. These ratios are the same as the census survival rates discussed in Chap. 4, but the notation is somewhat different:

$$_{n}\mathrm{CCR}_{x} = {}_{n}\mathrm{P}_{x+y,l} / {}_{n}\mathrm{P}_{x,b}$$

where $_{n}P_{x+y,l}$ is the population aged $x + y$ to $x + y + n$ in the most recent census (l), $_{n}P_{x,b}$ is the population aged x to $x + n$ in the second most recent census (b), and y is the number of years between the two most recent censuses ($l-b$). Using 2000 and 2010 as an example, the CCR for the population aged 20–24 in 2000 would be represented by:

$$_{5}\mathrm{CCR}_{20} = {}_{5}\mathrm{P}_{30,2010} / {}_{5}\mathrm{P}_{20,2000}$$

In the United States, the Hamilton-Perry method is most commonly used to project 5-year age cohorts in 10-year intervals. When mid-decade estimates (or censuses) are available, 5-year intervals also can be used. The method can easily be adapted to provide projections for additional characteristics such as race or ethnicity.

The basic formula for a Hamilton-Perry projection is:

$$_{n}\mathrm{P}_{x+z,t} = \left(_{n}\mathrm{CCR}_{x}\right)\left(_{n}\mathrm{P}_{x,l}\right)$$

Using data from the 2000 and 2010 censuses, for example, the formula for projecting the population aged 30–34 in the year 2020 is:

$$_{5}\mathrm{P}_{30,2020} = \left(_{5}\mathrm{CCR}_{20}\right)\left(_{5}\mathrm{P}_{20,2010}\right)$$

The quantity in the first set of parentheses is the CCR for the population aged 20–24 in 2000. If it is assumed this ratio will remain constant, the projection for the population 30–34 in 2020 is the population 20–24 in 2010 multiplied by the CCR.

When there are 10 years between censuses, 10–14 is the youngest age group for which projections can be made. How can the population aged 0–4 and 5–9 be projected? Hamilton and Perry (1962) used the most recent age-specific birth rates held constant over the projection interval. This procedure is valid, of course, but it requires data on births by age of mother; these data are not always available, especially for subcounty areas. We prefer a simpler approach that does not require any data beyond that available in the decennial census. This approach uses two child-woman ratios (CWRs) from the most recent census and applies them to the projected female population in the appropriate age groups.

For projecting the population 0–4, the CWR is defined as the population aged 0–4 divided by the female population aged 15–44. For projecting the population aged 5–9, the CWR is defined as the population aged 5–9 divided by the female population aged 20–49. The implementation of these ratios requires four projection equations—two for females and two for males:

$$\begin{aligned}&\text{Females } 0-4: \ {}_5\mathrm{FP}_{0,\mathrm{t}} = \left({}_5\mathrm{FP}_{0,\mathrm{l}}/{}_{30}\mathrm{FP}_{15,\mathrm{l}}\right)\left({}_{30}\mathrm{FP}_{15,\mathrm{t}}\right)\\ &\text{Males } 0-4: \ {}_5\mathrm{MP}_{0,\mathrm{t}} = \left({}_5\mathrm{MP}_{0,\mathrm{l}}/{}_{30}\mathrm{FP}_{15,\mathrm{l}}\right)\left({}_{30}\mathrm{FP}_{15,\mathrm{t}}\right)\\ &\text{Females } 5-9: \ {}_5\mathrm{FP}_{5,\mathrm{t}} = \left({}_5\mathrm{FP}_{5,\mathrm{l}}/{}_{30}\mathrm{FP}_{20,\mathrm{l}}\right)\left({}_{30}\mathrm{FP}_{20,\mathrm{t}}\right)\\ &\text{Males } 5-9: \ {}_5\mathrm{MP}_{5,\mathrm{t}} = \left({}_5\mathrm{MP}_{5,\mathrm{l}}/{}_{30}\mathrm{FP}_{20,\mathrm{l}}\right)\left({}_{30}\mathrm{FP}_{20,\mathrm{t}}\right)\end{aligned}$$

where *FP* is the female population, *MP* is the male population, *l* is the launch year, and *t* is the target year. For example, the formula for projecting females aged 0–4 in 2020 is:

$${}_5\mathrm{FP}_{0,2020} = \left({}_5\mathrm{FP}_{0,2010}/{}_{30}\mathrm{FP}_{15,2010}\right)\left({}_{30}\mathrm{FP}_{15,2020}\right)$$

Table 7.10 illustrates an application of the Hamilton-Perry method to project the number of females in Maricopa County in 2020 (shown in the unadjusted column). As the table shows, the method requires only a limited set of calculations. For example, the female population aged 10–14 in 2020 is calculated as:

$$(135,874/118,169)\,(138,502) = 159,254$$

Projections of the oldest age group differ slightly from projections for the other age groups. The calculations for the CCR require the summation of the three oldest age groups to get the population aged 75+ in the base year. A ratio of the population aged 85+ in the launch year (2010) to the population aged 75+ in the base year (2000) forms the basis of the projection of the population aged 85+ in the target year (2020):

$$\begin{aligned}&\mathrm{CCR}_{75+}: \mathrm{P}_{85+,\mathrm{l}}/\mathrm{P}_{75+,\mathrm{b}} = 38,170/(44,942 + 30,637 + 27,185) = 0.37143\\ &\text{Population } 85+ \text{ in } 2020: (0.37143)\,(45,824 + 37,217 + 38,170) = 45,021\end{aligned}$$

In this example, it is assumed that the launch year CWRs remain constant over the projection horizon. The two youngest age groups are thus projected by applying these CWRs to projected females aged 15–44 and 20–49:

$$\begin{aligned}&\text{Females } 15-44: 159,870 + 162,735 + 178,980 + 160,047 + 154,390 + 145,962\\ &\qquad = 961,984\\ &\text{Females } 20-49: 162,735 + 178,980 + 160,047 + 154,390 + 145,962 + 144,779\\ &\qquad = 946,893\\ &\text{Females } 0-4: (0.17471)\,(961,984) = 168,068\\ &\text{Females } 5-9: (0.17511)\,(946,893) = 165,810\end{aligned}$$

Table 7.10 Projected female population, Maricopa County, 2020 (Model III)

Age	2000 Population	2010 Population	CCR[a]	2020 Population Unadjusted[b]	2020 Population Adjusted[c]
0–4	118,169	138,502	n/a	168,068	160,824
5–9	116,278	138,369	n/a	165,810	158,663
10–14	107,992	135,874	1.14983	159,254	152,390
15–19	102,652	134,347	1.15539	159,870	152,980
20–24	106,048	129,341	1.19769	162,735	155,721
25–29	117,693	136,755	1.33222	178,980	171,266
30–34	115,287	131,224	1.23740	160,047	153,149
35–39	120,940	132,870	1.12895	154,390	147,736
40–44	112,714	128,235	1.11231	145,962	139,671
45–49	98,641	131,780	1.08963	144,779	138,539
50–54	88,376	124,017	1.10028	141,094	135,013
55–59	69,843	109,421	1.10929	146,182	139,881
60–64	56,526	100,312	1.13506	140,767	134,700
65–69	51,621	77,978	1.11648	122,166	116,901
70–74	50,132	58,416	1.03344	103,666	99,198
75–79	44,942	45,824	0.88770	69,221	66,238
80–84	30,637	37,217	0.74238	43,367	41,498
85+	27,185	38,170	0.37143	45,021	43,081
Total	1,535,676	1,928,652		2,411,379	2,307,449[d]
				Control	2,307,447
				Adj. factor	0.9568994

Child-woman ratio, 2010	
Ages 0–4/15–44	0.17471
Ages 5–9/20–49	0.17511

[a]2010 population age $(x + 10)$ / 2000 population age (x)

[b]Population in each of the two youngest age groups is calculated by multiplying the appropriate CWR by the appropriate population

[c]Unadjusted projection × Adj. factor

[d]Based on the average of projections from several trend extrapolation techniques applied to three base periods (1990–2010, 2000–2010, and 2005–2010). The average excluded the highest and lowest projections

This application of the Hamilton-Perry method holds CCRs constant over the projection interval; this approach has been used in several previous studies (Smith and Shahidullah 1995; Swanson et al. 2010). It is also possible to average together CCRs from several recent censuses or to extrapolate trends observed between censuses. However, time series approaches can be applied only if geographic boundaries remain constant over time. For many subcounty areas, this is difficult to achieve even for two censuses, much less for three or four (Pittenger 1976, p. 186). Another approach is to construct ratios of CCRs for small areas (e.g., census tracts) to CCRs for a larger area (e.g., county) and apply those ratios to projections of the larger area's CCRs. This approach is similar to the synthetic methods discussed in Chaps. 4 and 5.

7.3 Comparing Models I, II, and III

Theoretically, gross migration models are preferable to net migration models. Gross migration is closer to the true migration process than is net migration. It can be related to identifiable origin and destination populations, providing rates that approximate migration probabilities. In addition, gross migration models may provide more reasonable forecasts than net migration models in some circumstances, especially for long projection horizons and rapidly growing areas. However, gross migration models require more computations and more base data than net migration models. These data are unavailable for many areas and, given the relatively small sample sizes found in the ACS, may be less reliable as well. Although gross migration models are conceptually superior, net migration models are widely used in practice and generally can be tailored to produce forecasts that are as accurate as those produced by gross migration models.

It should be noted that the manner in which net migration rates are calculated can have a substantial impact on the resultant projections, especially in rapidly growing areas. In our example, we used the adjusted U.S. population as the denominator in constructing the rates. If we had used the Maricopa County population instead, the projected net migration flow for 2010–2015 would have been 4% higher (163,994 compared to 157,542); for 2035–2040, it would have been 56% higher (277,863 compared to 178,414). These differences occurred because the Maricopa County population is projected to grow more rapidly than the U.S. population. The analyst must keep this issue in mind when calculating net migration rates.

The major advantage of the Hamilton-Perry method compared to both gross and net migration models is that it has much smaller data requirements. Instead of mortality, fertility, migration, and population data, the Hamilton-Perry method simply requires population data by age and sex from two consecutive censuses (or estimates). Consequently, it is much quicker, easier, and cheaper to implement than a full-blown cohort-component model and is particularly useful for small-area projections.

As noted in Chap. 2, the 2000 census was the first to allow respondents to list themselves as belonging to more than one racial category. As a result, racial data since 2000 are inconsistent with racial data prior to 2000. In addition, racial classifications from the decennial census are not completely consistent with classifications used for vital statistics data, making it difficult to develop reliable estimates of components of change for racial groups. Both of these issues create problems for cohort-component projections. Because it can be based solely on data from the two most recent censuses, the Hamilton-Perry method avoids these problems and provides a viable alternative to a full-blown cohort-component model, especially for projections of the multi-racial population (Swanson 2013).

One caveat regarding the Hamilton-Perry method should be mentioned. This method is essentially a set of cohort growth rates applied to a beginning population. As we show in Chap. 13, constant growth rates can lead to large forecast errors and a strong upward bias when applied to rapidly growing places. Consequently, we believe it is generally advisable to control Hamilton-Perry projections to independent projections of total population (Smith and Shahidullah 1995; Swanson et al. 2010). Such an adjustment is illustrated in the last column of Table 7.10. When this adjustment is made, the Hamilton-Perry method projects only the age composition of the population, not its total size.

The three migration models used in our examples were based on data covering three different lengths of base period: 1 year for Model I, 5 years for Model II, and 10 years for Model III. The analyst must decide whether the migration rates drawn from a particular base period are likely to provide reasonable projections of future migration flows. In most circumstances, we believe it is advisable to take an average of rates from several different base periods, especially for long-range projections. The impact of the length of the base period on forecast accuracy is discussed in Chap. 13.

7.4 Conclusions

The cohort-component method is a mainstay in the demographer's toolbox and is not likely to relinquish its lofty position any time soon. It provides a theoretically complete model that accounts for the individual components of growth and for the impact of changes in demographic composition over time. It can incorporate many different application techniques, types of data, and assumptions regarding future trends. Perhaps most important, it provides projections not only of total population but of the components of growth and changes in demographic composition as well.

The cohort-component method has its limitations, however. Perhaps the most important is that it is very data-intensive and requires a large number of computations. A full cohort-component model requires mortality, fertility, migration, and population data by age and sex (and perhaps other characteristics as well). Collecting, verifying, and cleaning up these data is a tedious and time-consuming process. The number of computations involved in applying the method is very large. Consequently, the cohort-component method is relatively expensive to apply. As we show in the next chapter, other projection methods are simpler, less data-intensive, and less costly.

We believe it is helpful to compare cohort-component projections with projections produced by other projection methods. If the differences are large, possible explanations for those differences must be considered. In some circumstances, it may be beneficial to control the projections of demographic characteristics (e.g., age, sex, race) coming from the cohort-component method to projections of total population coming from other projection methods. Controlling is most likely to be beneficial for rapidly growing areas and long projection horizons, especially when projections are made using net migration models or the Hamilton-Perry method.

Large data requirements preclude the use of some forms of the cohort-component method at some levels of geography. Although seldom a problem for states and large counties, the lack of data presents a formidable challenge for small counties and subcounty areas. Birth and death data are routinely available for counties but not for most subcounty areas. Migration data are an even greater problem. ACS migration data are quite limited, especially at the subcounty level. Although PUMS files provide detailed migration information, they are often based on a small sample size and are available only for places with at least 100,000 residents. IRS migration data are not tabulated below the county level and do not provide breakdowns of demographic characteristics. Because of these data problems, the Hamilton-Perry method is often the best cohort-component model to use for subcounty projections.

A final limitation of the cohort-component method is that—although it provides the mathematical framework for making projections for cohorts and components of growth—it provides no guidance regarding the choice of assumptions that will lead to reasonable forecasts. Will mortality rates decline over the next 20 years? If so, how rapidly? Will fertility rates go up or down? Will migration follow the patterns observed over the last 10 years or revert to the patterns observed during the previous 10 years? What economic, social, cultural, political, or biological factors might cause recent demographic trends to change course? Nothing in the cohort-component method itself provides answers to these questions.

As Chaps. 4, 5 and 6 suggest, we must seek answers to these questions elsewhere. Models based solely on demographic factors are limited in the range of theoretical, policy, and planning questions they can address. However, structural and microsimulation models can be developed that incorporate explanations of the determinants of population growth directly into the projection method (see Chap. 9). These models can be applied within the framework of the cohort-component method, greatly increasing its usefulness for a variety of purposes. This highlights one of the most important attributes of the cohort-component method; namely, its flexibility. The cohort-component method can accommodate a wide variety of application techniques and data sources. It is not surprising that it continues to be the most widely used of all the population projection methods.

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Chapter 8
Extrapolation Methods

Early versions of the cohort-component method were developed in the late nineteenth and early twentieth centuries, but the method did not become widely used until the middle of the twentieth century. Before that time projections were typically made by extrapolating historical population trends into the future, using one or more of a number of mathematical formulas. Projections based on trend extrapolations were made by such eminent "demographers" as Benjamin Franklin, Thomas Jefferson, and Abraham Lincoln (Dorn 1950). In spite of their simplicity and lack of theoretical content and demographic detail, early applications of this approach often produced reasonably accurate forecasts of total population, even for projection horizons extending well into the future (Pritchett 1891; Pearl and Reed 1920).

Trend extrapolation methods were largely overshadowed by other methods by the middle of the twentieth century, but have made a comeback in recent years as new methods were developed and detailed evaluations of forecast accuracy and utility were conducted. Relatively low costs and small data requirements make these methods particularly useful for small-area projections. We discuss other characteristics of trend extrapolation methods (including their forecast accuracy) in Chaps. 12 and 13.

The defining characteristic of trend extrapolation methods is that future values of any variable are determined solely by its historical values; that is, these methods assume that change over the projection horizon will follow previous trends. In this chapter, we describe and illustrate a number of trend extrapolation methods that have been used for state and local population projections. Descriptions of extrapolation methods used in other fields can be found in Armstrong (2001), Granger (1989), Mahmoud (1984), Makridakis et al. (1989), and Schnaars (1986).

There are many different ways to measure historical population values and project them into the future using trend extrapolation methods (Davis 1995; Irwin 1977; Isserman 1977; Pittenger 1976; Rayer 2007). It is convenient to organize them into three categories. S*imple extrapolation methods* are those that have simple mathematical structures and require data for only two points in time. We cover three simple methods: linear extrapolation, geometric extrapolation, and exponential extrapolation. *Complex extrapolation methods* require data from a number of

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points in time, have more complicated mathematical structures, and require statistical estimation of the model's parameters. We cover five complex methods: linear trend models, polynomial curve fitting, exponential curve fitting, logistic curve fitting, and ARIMA time series models. *Ratio extrapolation methods* express the population of a smaller unit as a proportion of the population of a larger unit; for example, a county's population can be expressed as a proportion of a state's population. We cover three ratio methods: constant-share, shift-share, and share-of-growth.

We illustrate these methods using data from 1990 to 2010 for Franklin County and Grays Harbor County in the State of Washington. Franklin County is located in eastern Washington and contains a diverse economy rooted in agriculture, bio- and high-technology, and manufacturing. The U.S. Department of Energy's Hanford site is located near Franklin County. Grays Harbor is a coastal county in western Washington whose economy is based primarily on wood and paper products and seafood processing industries; this area has been impacted by a decline in the timber industry.

Table 8.1 and Fig. 8.1 show the base data for Franklin County and Grays Harbor County. Franklin County was the fastest growing county in the state between 1990 and 2010, growing by 108.6%, while Grays Harbor County was one of the slowest growing, growing by only 13.4%. In 1990, Grays Harbor County had 26,702 more people than Franklin County. By 2010, the population of Franklin County exceeded that of Grays Harbor County by almost 5,400 people. Table 8.1 also includes the state-level data needed to apply the ratio methods.

For consistency, we use a 20-year base period for all 11 methods. For methods requiring only two data points, we use the population in 1990 and 2010. For complex methods requiring more data, we use all of the annual data between 1990 and 2010. We make projections for both counties from 2010 to 2040 using each of the 11 methods.

Although there are exceptions, trend extrapolation methods are used most frequently for projections of total population. As discussed in Chaps. 4, 5, 6, they can also be used for projecting individual components of change in the cohort-component method. We focus primarily on projections of total population in this chapter, but also provide an example of a ratio method used for projecting population by racial/ethnic group.

8.1 Simple Extrapolation

8.1.1 Linear

The linear extrapolation method (LINE) assumes that the population will change by the same number of persons in the future as it did in the past. Past and future time periods are usually measured by years, but can be measured by decades or other

Table 8.1 Population of Washington and Franklin and Grays Harbor Counties, 1990–2010

Year	Washington	Franklin	Grays Harbor
1990	4,866,692	37,473	64,175
1991	5,021,335	38,522	64,309
1992	5,141,177	39,077	64,636
1993	5,265,688	40,092	64,930
1994	5,364,338	41,280	65,441
1995	5,470,104	42,516	65,820
1996	5,567,764	43,694	66,172
1997	5,663,763	45,180	66,553
1998	5,750,033	46,465	66,568
1999	5,830,835	47,900	66,766
2000	5,894,143	49,347	67,194
2001	5,970,330	50,473	68,709
2002	6,059,316	52,286	69,229
2003	6,126,885	54,907	69,445
2004	6,208,515	58,576	70,069
2005	6,298,816	62,572	70,812
2006	6,420,258	66,371	71,582
2007	6,525,086	69,582	72,038
2008	6,608,245	72,230	72,295
2009	6,672,159	75,111	72,569
2010	6,724,540	78,163	72,797
Avg. annual change	92,892.4	2,034.5	431.1
Percent change	38.2%	108.6%	13.4%
Avg. annual growth rate[a]	1.6%	3.7%	0.6%

Sources: Intercensal Estimates of April 1 Population and Housing, 2000–2010. Washington State OFM, Forecasting Division, Oct. 2011
Intercensal Estimates of April 1 Population and Housing, 1990–2000. Washington State OFM, Forecasting Division, 2002–2003
[a]Exponential growth rate

intervals as well. Using years as the time period, average annual numeric change during the base period is computed as:

$$\mathrm{AANC} = (\mathrm{P_l} - \mathrm{P_b})/\mathrm{y}$$

where *AANC* is the average annual numeric change during the base period; P_l is the population in the launch year; P_b is the population in the base year; and y is the number of years in the base period (for a review of terminology, see Box 1.3). Population projections using the linear extrapolation method are computed as:

$$\mathrm{P_t} = \mathrm{P_l} + (\mathrm{z})\ (\mathrm{AANC})$$

where P_t is the population in the target year and z is the number of years in the projection horizon.

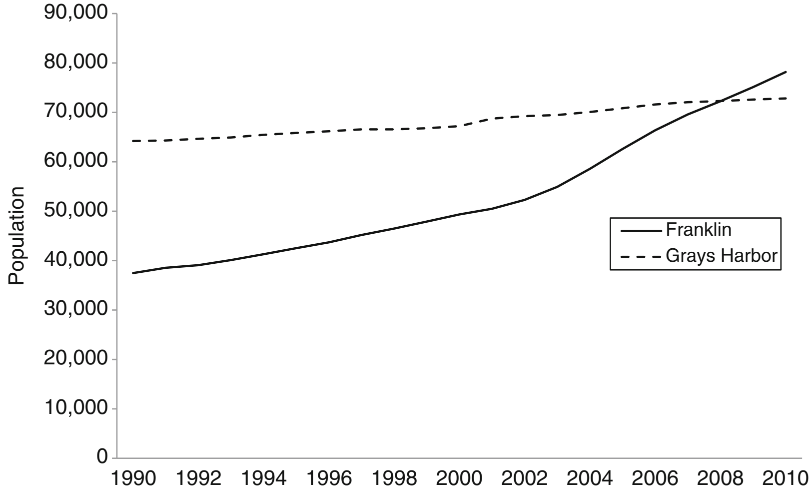

Fig. 8.1 Total population, Frankin and Grays Harbor Counties, 1990–2010

The average annual numeric change between 1990 and 2010 and the 2015 population projection for Franklin County are:

$$\text{AANC} = (78{,}163 - 37{,}473)/20 = 2{,}034.5$$
$$P_{2015} = 78{,}163 + (5)\ (2{,}034.5) = 88{,}336$$

The corresponding calculations for Grays Harbor County are:

$$\text{AANC} = (72{,}797 - 64{,}175)/20 = 431.1$$
$$P_{2015} = 72{,}797 + (5)\ (431.1) = 74{,}953$$

Different base periods and projection horizons can be accommodated by simply changing the years used to define the base year (b), launch year (l), and target year (t). For example, projections for 2025 are:

$$\text{Franklin County} : 78{,}163 + (15)\ (2{,}034.5) = 108{,}681$$
$$\text{Grays Harbor County} : 72{,}797 + (15)\ (431.1) = 79{,}264$$

8.1.2 Geometric

The geometric extrapolation method (GEO) assumes that the population will change at the same annual percentage rate over the projection horizon as during the base period. The average geometric rate of population change during the base period is computed as:

$$r = (P_l/P_b)^{(1/y)} - 1$$

where r is the average geometric rate of change; P_l is the population in the launch year; P_b is the population in the base year; and y is the number of years in the base period. Given this formula, a population projection using the GEO method is expressed as:

$$P_t = (P_l)\ (1 + r)^z$$

The annual rate of geometric change between 1990 and 2010 and the 2015 population projection for Franklin County are:

$$r = (78{,}163/37{,}473)^{(1/20)} - 1 = 0.03744$$
$$P_{2015} = (78{,}163)\ (1 + 0.03744)^5 = 93{,}933$$

The corresponding calculations for Grays Harbor County are:

$$r = (72{,}797/64{,}175)^{(1/20)} - 1 = 0.00632$$
$$P_{2015} = (72{,}797)\ (1 + 0.00632)^5 = 75{,}127$$

8.1.3 Exponential

Geometric growth rates are based on compounding at discrete time intervals (in this example, once each year). Another approach to calculating growth rates is based on continuous compounding (EXPO). This approach more nearly represents the dynamics of population growth because growth generally occurs continuously rather than at discrete intervals. Under this approach, the annual growth rate is computed as:

$$r = [\ln\ (P_l/P_b)]/y$$

where r is the average annual exponential rate of change; *ln* is the natural logarithm; P_l is the population in the launch year; P_b is the population in the base year; and y is the number of years in the base period. A population projection using the exponential change method is expressed as:

$$P_t = (P_l)\ (e^{rz})$$

where e is the base of the system of natural logarithms (approximately 2.71828).

The annual rate of exponential change from 1990 to 2010 and the 2015 population projection for Franklin County are:

$$r = \ln\ (78{,}163/37{,}473)/20 = 0.03676$$
$$P_{2015} = (78{,}163)\ \left(e^{(0.03676)\ (5)}\right) = 93{,}934$$

The corresponding calculations for Grays Harbor County are:

$$r = \ln(72{,}797/64{,}175)/20 = 0.00630$$
$$P_{2015} = (72{,}797)\left(e^{(0.00630)\,(5)}\right) = 75{,}127$$

Growth rates based on an exponential model are similar to those based on a geometric model, especially for places that are not growing rapidly. The average annual geometric and exponential growth rates from 1990 to 2010 for slowly growing Grays Harbor County are 0.632% and 0.630%, respectively. For the more rapidly growing Franklin County, they are 3.744% and 3.676%. Exponential growth rates are always smaller than geometric growth rates because they reflect continuous compounding rather than compounding at discrete intervals.

For both areas, the EXPO projections are almost identical to the GEO projections for the year 2015. Even when carried out to 2040, the projections are identical for Grays Harbor County and differ only by four for Franklin County. If applied consistently, the GEO and EXPO methods will provide virtually identical projections. Rather than repeating the same results, we report solely on the EXPO method in the remainder of this chapter.

Both the GEO and EXPO methods can lead to very high projections in rapidly growing places. Consider an example from Palm Coast, a rapidly growing city in Florida. A continuation of its 2000–2010 exponential growth rate (6.5% per year) would cause its population to double about every 11 years. In 40 years its population would be more than 12 times larger than its 2010 population (95,696), reaching almost 1,190,000; in 80 years, it would be 154 times larger (almost 15 million). Clearly, these are not reasonable projections. These two methods must be used cautiously for long-range projections, especially for rapidly growing places.

8.2 Complex Methods

Complex extrapolation methods differ from simple methods in several ways. They require additional time points over the base period and thus can provide a more complete picture of the historical pattern of population change. Their more complex mathematical structures provide a wider range of possible assumptions regarding population trends than simpler methods. In addition, the statistical algorithms for estimating their parameters provide a basis for constructing prediction intervals around the population forecasts (Bongaarts and Bulatao 2000, Chap. 7; Tayman 2011). However, complex extrapolation methods are considerably more difficult to implement than simple trend or ratio methods. We compare the forecast accuracy of simpler and more complex methods in Chap. 13.

Three basic steps are typically followed when applying complex extrapolation methods. The first is to assemble historical population data at equal time intervals during the base period. Population projections typically use annual intervals (Pflaumer 1992; Saboia 1974; Tayman et al. 2007) or intervals between censuses

(Isserman 1977; Leach 1981). The data must be based on consistently defined geographic boundaries for each time point; adjustments will be required in areas that have experienced shifts in boundaries, which is often the case for subcounty areas.

The second step is to choose a mathematical model and estimate its parameters through a process known as *curve fitting* (Alinghaus 1994). The choice of a particular model also reflects judgments about the nature of population change and the most likely future population trend (Davis 1995, p. 17). Typically, graphs, statistical correlation measures and tests, and analysis of residuals are used to evaluate how well a model fits the historical data; however, a close fit does not guarantee an accurate (or even a reasonable) forecast.

The essential assumption underlying both simple and complex extrapolation methods is that the functional relationship between historical population change and time will remain constant over the course of the projection horizon. For complex methods, this implies that the model's coefficients will describe future relationships as well as they described past relationships. If these relationships change, projections are not likely to provide accurate forecasts regardless of how well the model fit the data during the base period.

The final step is to use the mathematical model and estimated parameters to prepare the population projections. In complex extrapolation models, population is the dependent variable and time is the independent variable. In this section, we describe and illustrate five complex extrapolation models: linear trend, polynomial curve fitting, exponential curve fitting, logistic curve fitting, and ARIMA time series models. The projections illustrating these methods are based on 21 data points for Franklin County and Grays Harbor County that represent annual population data from 1990 to 2010. For ease of interpretation, we express time as integers ranging from 1 to 51 (1 = 1990, 2 = 1991, …, 21 = 2010, 22 = 2011, …, 51 = 2040). The decision on the measurement of time is not substantively important, as long as a consistent coding scheme is used for both the base and projection periods.

8.2.1 Linear Trend

The linear trend model is the simplest and most familiar of the complex trend extrapolation methods. This model assumes that the population will change by a constant numerical amount, as determined by its historical population change. This assumption is identical to that underlying the simple linear method discussed earlier, but is operationalized differently. The linear trend model is based on the equation for a straight line:

$$Y = a + bX$$

where *Y* is the dependent variable (e.g., population); *X* is the independent variable (e.g., time); *a* is the intercept term; and *b* is the slope. The terms *Y* and *X* are the model's variables. They represent the data used in estimating the model and take on values that vary with each observation. The terms *a* and *b* are the model's parameters (or coefficients). They represent the statistical relationships between the independent and dependent variables. Their values remain constant for any particular application of the model but vary from one application to another.

In a diagram, the intercept term reflects the population value where the line estimated by the model crosses the Y-axis (i.e., $X = 0$). The slope measures the projected annual change in population. A positive slope reflects a growing population and a negative slope reflects a declining population. Ordinary least squares (OLS) regression techniques are used to estimate *a* and *b*.

For Franklin County, the estimated intercept and slope are 30,635.0 and 2,028.1, respectively. The slope indicates that the county's population will increase by about 2,028 annually over the projection horizon; this is very close to the average annual increase of 2,034 occurring over the base period. The equation has an adjusted r^2 of 0.937. The adjusted r^2 is a measure of the "goodness of fit" of an equation, showing the proportion of variation in the dependent variable that can be attributed to variation in the independent variable(s). Values for this measure fall between 0 and 1. The high value for Franklin County shows that a linear model fits the historical data quite well.

For Grays Harbor County, the estimated intercept and slope are 62,982.5 and 473.9, respectively. The adjusted r^2 is 0.976, showing that a linear model fits the data slightly better for Grays Harbor County than for Franklin County. The slope indicates that Franklin County's population will increase by about 474 annually over the projection horizon; this is higher than the average annual increase of 431 occurring over the base period.

Population projections can be constructed by plugging the estimated parameters into the model as follows:

$$P_t = a + bX_t + cf$$

where P_t is the population in the target year; *a* and *b* are the estimated parameters; X_t is the time value corresponding to the target year; and *cf* is the calibration factor.

The calibration factor requires explanation. In any curve-fitting procedure, it will be unusual for the estimated and observed values in the launch year to be identical. The calibration factor is an adjustment that makes the projected population consistent with the launch year population. The calibration factor is computed by subtracting the predicted population from the observed population in the launch year. If the difference is negative (positive), the estimates will be adjusted downward (upward) by a constant amount. This adjustment produces a parallel shift in the trend line that makes it pass directly through the launch year population. Other adjustment procedures can also be used (Isserman 1977; Treyz 1995, pp. 55–57).

We recommend making such adjustments when applying complex extrapolation methods.

The OLS regression results, calibration factors, and 2015 population projection for Franklin County, using the value of 26 for time, are:

$$\text{cf} = 78{,}163 - 73{,}224 = 4{,}939$$
$$P_{2015} = 30{,}635.0 + (2{,}028.1)\,(26) + 4{,}939 = 88{,}305$$

The corresponding results for Grays Harbor County are:

$$\text{cf} = 72{,}797 - 72{,}935 = -138$$
$$P_{2015} = 62{,}982.5 + (473.9)\,(26) - 138 = 75{,}166$$

Projections for different target years can be made by changing the X value in the equation. For example, a projection for 2025 would use an X value of 36 and a projection for 2040 would use an X value of 51. In most instances, projections from the linear trend model will be similar to the projections from the LINE method.

8.2.2 Polynomial Curve Fitting

Like the EXPO and GEO methods discussed earlier, polynomial curves can be useful for basing projections on non-linear patterns (i.e., patterns in which population change is not a constant numeric value). The general formula for a polynomial curve is:

$$Y = a + b_1X + b_2X^2 + b_3X^3 + \ldots + b_nX^n$$

Again, Y and X refer to population and time, respectively. In contrast to the linear trend, a polynomial curve has more than one term for the time variable; consequently there are more parameters to estimate. These terms are represented by raising the time variable to different powers. The coefficients for a polynomial curve ($a, b_1, b_2, \ldots, b_n$) can be estimated using OLS regression techniques. These coefficients include a measure of the linear trend (b_1) and measures of the non-linear pattern ($b_2, b_3, \ldots., b_n$). Polynomial curves can have any number of terms on the right-hand side of the equation. The highest exponent in the equation is called the *degree* of the polynomial. The linear model previously discussed is a first degree polynomial; a second degree contains X and X^2; a third degree polynomial contains X, X^2, and X^3; and so forth. Although polynomial curves of any degree can be used, polynomials higher than third degree are seldom used for population projections.

To illustrate a projection based on a polynomial curve, we use a second degree polynomial (sometimes called a *quadratic function*). This function includes time (the linear term) and time squared (also called the *parabolic term*) on the right-hand side of the equation:

$$P_t = a + b_1X_t + b_2{X_t}^2 + cf$$

A quadratic curve can produce a variety of growth scenarios, depending on the signs and magnitudes of the two slope coefficients (see Fig. 8.2). Positive values for both coefficients will result in the population growing at an increasing rate over the projection horizon, while negative values for both coefficients will result in a population declining at an increasing rate. A positive linear term and a negative quadratic term will cause a population to increase at a decreasing rate; eventually this population will stop growing and start declining. A negative linear term and positive quadratic term will cause a population to decline at a decreasing rate; eventually this population will stop declining and start growing. As with EXPO and GEO, projections based on a quadratic curve can lead to very high (or low) projections for places that were growing (or declining) rapidly during the base period.

We use OLS regression techniques to estimate the coefficients in the quadratic equation. The regression results, calibration factor, and 2015 population projection for Franklin County are:

$$cf = 78{,}163 - 78{,}961 = -798$$
$$P_{2015} = 38{,}274.3 + (35.2)\,(26) + (90.6)\left(26^2\right) - 798 = 99{,}637$$

The corresponding results for Grays Harbor County are:

$$cf = 72{,}797 - 73{,}443 = -646$$
$$P_{2015} = 63{,}658.4 + (297.6)\,(26) + (8.0)\left(26^2\right) - 646 = 76{,}158$$

For Franklin County, the parabolic term is significant at $\alpha = 0.05$ and the adjusted r^2 for the equation is 0.995, or 0.058 points higher than for the linear model. This indicates that the parabolic term helps describe population growth in Franklin County. Moreover, the parabolic coefficient is substantially larger than the coefficient on the linear term, which loses its statistical significance. The population projection for Franklin County is driven primarily by the quadratic, non-linear term and the quadratic model yields the highest projection of any trend extrapolation method (see Table 8.7).

For Grays Harbor County, the squared term in significant at $\alpha = 0.05$ but the adjusted r^2 is only 0.008 points higher than for the linear model. In contrast to the quadratic model for Franklin County, the coefficient of the linear term in the Grays Harbor equation (297.6) is much larger than the coefficient of the quadratic term (8.0). Yet, the significance and positive value of the quadratic coefficient has a notable impact on the projection for Grays Harbor County, which is generally higher than for the other extrapolation methods (see Table 8.7).

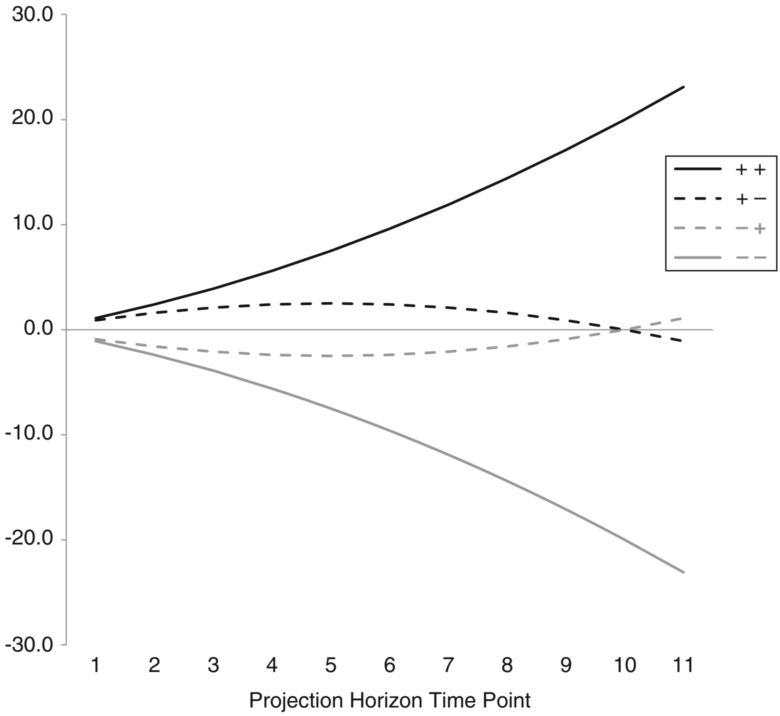

Fig. 8.2 Patterns of change from a quadratic curve based on signs of the linear and squared terms (Derived from the quadratic function using coefficients of 1.0 and 0.1 on the linear and squared terms and time values from 1 to 11)

8.2.3 Exponential Curve Fitting

Non-linear trends in the historical data can also be projected using curves based on logarithmic or other transformations of the base data (Draper and Smith 1981, Chap. 5; Isserman 1977; Stock and Watson 2003, Chap. 6). Common transformations include reciprocal functions using the inverse of time; power functions using the natural logarithms of time and population; logarithmic functions using the natural logarithm of time; and exponential functions using the natural logarithm of population. We use the exponential function to illustrate the use of data transformations:

$$\ln(Y) = a + bX$$

Similar to the linear trend model, the exponential curve has only one variable for time (X), but the population (Y) is transformed by taking its natural logarithm. Using the transformed population variable, OLS is used to estimate the parameters (*a* and *b*) for the exponential model. The slope coefficient is interpreted as the average annual rate of change.

Solving the regression equation with the future value of time yields a projection of the natural logarithm of the population:

$$\ln\left(\mathrm{P_t}\right) = \mathrm{a} + \mathrm{b}(\mathrm{X_t}) + \mathrm{cf}$$

The projection of the population itself is then obtained by applying the rules of natural logarithms; that is, *e* is raised to the power based on the regression results (adjusted for re-transformation bias):

$$\mathrm{P_t} = \left(\mathrm{e}^{\ln\left(\mathrm{P}_t\right)(\mathrm{sme})}\right)$$

The population cannot be projected simply by taking the exponential function of $ln\ (P_t)$ because of retransformation bias (Manning 1998). To correct for this bias, $ln\ (P_t)$ is multiplied by a "smearing estimator" (*sme*) prior to taking the exponential function. The *sme* is calculated by computing the mean of the antilog of the residuals Duan (1983), and it usually yields a value between 1 and 2. The *sme* is very close to 1.0 in our examples, which means the level of bias is well under 1%. We believe the retransformation bias will usually be small in complex exponential models for projecting population.

The regression results, calibration factors, smearing estimators, and 2015 population projection for Franklin County are:

$$\mathrm{cf} = 11.26655 - 11.22590 = 0.04065$$
$$\mathrm{sme} = 1.000653$$
$$\ln\left(\mathrm{P_{2015}}\right) = [10.43601 + (0.03761)\,(26) + 0.04065]\,(1.000653) = 11.46210$$
$$\mathrm{P_{2015}} = \mathrm{e}^{11.46210} = 95{,}045$$

The corresponding results for Grays Harbor County are:

$$\mathrm{cf} = 11.19543 - 11.19857 = -0.00314$$
$$\mathrm{sme} = 1.000018$$
$$\ln\left(\mathrm{P_{2015}}\right) = [11.05297 + (0.00693)\,(26) - 0.00314]\,(1.000018) = 11.23029$$
$$\mathrm{P_{2015}} = \mathrm{e}^{11.23029} = 75{,}379$$

The exponential model fits the data well for both counties. The adjusted r^2 is 0.979 for Grays Harbor County and 0.974 for Franklin County. The slope coefficients indicate that the populations of Franklin County and Grays Harbor County will increase by approximately 3.8% and 0.7% annually over the projection horizon, respectively. These growth rates are slightly higher than those observed over the base period (3.7% and 0.6%).

8.2.4 Logistic Curve Fitting

The extrapolation models considered so far are not constrained by any limits to change. In these methods, population growth (or decline) can go on forever (or over the length of the forecast horizon, anyway). In many instances this will not be a reasonable assumption. In particular, the compounding effects of exponential or geometric growth rates and some nonlinear models can lead to very high projections when carried too far into the future.

The logistic curve—one of the best-known growth curves in demography—deals with this problem by including an explicit ceiling (or upper limit) on the size of the population (Pittenger 1976, pp. 62–67; Romaniuc 1990). It depicts an S-shaped pattern representing an initial period of slow growth rates, followed by a period of increasing growth rates, and finally a period of declining growth rates that approach zero as a population approaches its upper limit. The idea of limits to growth is intuitively plausible and is consistent with Malthusian and other theories of constrained population growth.

Due in large part to the work of Pearl and Reed (1920) and Yule (1925), the logistic curve was a popular projection method in the early decades of the twentieth century. Although its usefulness for projections has been questioned (Brass 1974; Marchetti et al. 1996), several studies have shown that logistic curves often provide reasonably accurate population forecasts (Dorn 1950; Leach 1981). Other curves containing asymptotic ceilings on population size include modified exponential and Gompertz models (Davis 1995, Chap. 3; Pittenger 1976, pp. 67–68). In addition, the modified exponential and hyperbolic curves may be useful for projecting rapidly declining populations because they set lower limits on population size (Davis 1995, Chap. 3).

To implement our logistic model, we add a calibration factor to the three-parameter logistic curve suggested by Keyfitz (1968, p. 215):

$$\mathrm{Y} = a/\left[1 + \mathrm{b}\left(\mathrm{e}^{-\mathrm{cX}}\right)\right] + \mathrm{cf}$$

where *Y* is population, *X* is time, *a* is the upper asymptote (or population limit); *b* and *c* are parameters that define the shape of the logistic curve; *e* is the base of the natural logarithm; and *cf* is the calibration factor. In using a logistic curve for population projections, one must determine the magnitude of the upper asymptote and the time required to reach it. These factors are based on the values of the three parameters (*a, b,* and *c*), which can be estimated using iterative least squares techniques (Keyfitz 1968, pp. 215–218). Other computational procedures for estimating these parameters are shown in Pittenger (1976, pp. 62–66) and Shryock and Siegel (1973, pp. 382–385). Unlike parameters in an ordinary regression model, the estimated parameters in a logistic model may not be consistent with realistic interpretations of population growth (e.g., *a* may not represent a reasonable upper limit for population size). Other specifications are available for the logistic curve, including some with more than three parameters (Pielou 1969, pp. 19–32; Sieber and Wild 1989, p. 331).

Some software packages (e.g., SPSS) require an independent estimate of the upper asymptote before the model's other parameters can be estimated, whereas other packages (e.g., NCSS) estimate all parameters within the context of the model. We used the NCSS statistical package because it does not require an independent estimate of the upper asymptote. This is a useful feature because it takes some of the guesswork out of the estimation process. For purposes of comparison, we ran the logistic model using both statistical packages and obtained almost identical projections when the NCSS estimate of the upper asymptote was used in the SPSS logistic curve algorithm.

For a three-parameter logistic model, the regression results, calibration factors, and 2015 population projection for Franklin County are:

$$\mathrm{cf} = 78{,}163 - 76{,}577 = 1{,}586$$
$$\mathrm{P}_{2015} = 1{,}000{,}000{,}000/\left[1 + (30{,}176.6)\left(\mathrm{e}^{(-0.03989)\ (26)}\right)\right] + 1{,}586 = 95{,}065$$

The corresponding results for Grays Harbor County are:

$$\mathrm{cf} = 72{,}797 - 73{,}053 = -256$$
$$\mathrm{P}_{2015} = 12{,}973{,}757.9/\left[1 + (204.6)\left(\mathrm{e}^{(-0.00701)\ (26)}\right)\right] - 256 = 75{,}388$$

The logistic model fits the data well for both counties. The adjusted r^2 for Grays Harbor County and Franklin County are 0.981 and 0.978, respectively. The projections are shown in Table 8.2. Although the estimated *a* parameters are not reasonable estimates of upper population limits for either county, the projections themselves seem reasonable and fall within the range of projections from the other extrapolation methods (see Table 8.7).

To illustrate the impact of imposing more realistic values for the upper limit, we re-estimated the logistic model using *a* values of 250,000 and 90,000 for Franklin County and Grays Harbor County, respectively. These upper limits are in line with the highest projections for 2040 shown in Table 8.7. As shown in the top panel of Table 8.2, reducing the upper limit has a substantial impact on the projections, most notably for Franklin County where the 2040 projection falls by more than 90,000 persons (35.6%). The 2040 projection for Grays Harbor County falls by about 8,000 persons (8.7%).

Examining the changes over 5-year periods, we see that under the initial model, numeric changes in both counties increase continuously over the projection horizon, reflecting no asymptotic pattern (bottom panel of Table 8.2). When more realistic upper limits are imposed, the asymptotic nature of the logistic curve becomes apparent. For Franklin County, the 5-year change peaks at 15,007 for 2025–2030 and drops to 14,200 by 2035–2040. For Grays Harbor County, the change peaks 5 years earlier (2020–2025) at 1,591 and declines to 1,140 by 2035–2040.

Table 8.2 Population projections: Logistic curve fitting, Franklin and Grays Harbor Counties, 2015–2040

Total population						
	Franklin County			Grays Harbor County		
Target year	Upper Asymptote[a]	Upper Asymptote[b]	Percent difference	Upper Asymptote[c]	Upper Asymptote[d]	Percent difference
2015	95,065	91,302	−4.0	75,391	74,736	−0.9
2020	115,696	105,417	−8.9	78,074	76,498	−2.0
2025	140,880	120,177	−14.7	80,850	78,089	−3.4
2030	171,622	135,184	−21.2	83,725	79,519	−5.0
2035	209,146	150,003	−28.3	86,700	80,798	−6.8
2040	254,950	164,233	−35.6	89,781	81,938	−8.7
Population change						
	Franklin County			Grays Harbor County		
Projection horizon	Upper Asymptote[a]	Upper Asymptote[b]	Percent difference	Upper Asymptote[c]	Upper Asymptote[d]	Percent difference
2010–2015	16,902	13,139	−22.3	2,594	1,939	−25.3
2015–2020	20,631	14,115	−31.6	2,683	1,762	−34.3
2020–2025	25,184	14,760	−41.4	2,776	1,591	−42.7
2025–2030	30,742	15,007	−51.2	2,875	1,430	−50.3
2030–2035	37,524	14,819	−60.5	2,975	1,279	−57.0
2035–2040	45,804	14,230	−68.9	3,081	1,140	−63.0

[a]Asymptote = 1.0 billion
[b]Asymptote = 250,000
[c]Asymptote = 12.4 million
[d]Asymptote = 90,000

Logistic models are consistent with various theories of population growth and with empirical evidence from many situations in which populations (including non-human populations such as yeast cells and fruit flies) move from low to high to low rates of growth. However, they are dependent upon the same basic assumptions as other trend extrapolation methods; namely, that future population changes emerge directly and smoothly from past population changes and that historical relationships remain constant over time. In addition, it is difficult to develop reliable estimates of the model's parameters, and relatively small differences in the parameters (especially the upper limit) can lead to large differences in population projections. Because of these problems, logistic models are no longer widely used for population projections.

8.2.5 ARIMA Models

The last complex extrapolation method is the Autoregressive Integrated Moving Average (ARIMA) model. Popularized by Box and Jenkins (1976), ARIMA models have been used extensively in the analysis and projection of demographic attributes measured over time (Land 1986). They have been applied to individual components of population change (Carter and Lee 1986; de Beer 1993; McNown and Rogers 1989) as well as to estimates of total population (Alho and Spencer 1997; Saboia 1974; Pflaumer 1992; Tayman et al. 2007). Some believe ARIMA models are preferable to regression-based extrapolation methods because they produce more accurate coefficient estimates and smaller errors over the projection horizon (Granger and Newbold 1986, pp. 205–215; Jenkins 1979, pp. 88–94; McDonald 1979). Furthermore, the dynamic and stochastic framework of ARIMA models provides a statistical basis for developing probabilistic intervals around a specific population projection (Box and Jenkins 1976, Chap. 5; Nelson 1973, Chap. 6).

However, the methods used in ARIMA modeling are considerably more complex than those used in other extrapolation methods, making them more difficult to implement and explain to data users. We provide a general overview of ARIMA modeling in this section, but suggest that readers consult standard texts for more details on implementing these models (Box and Jenkins 1976; Brockwell and Davis 2002; Chatfield 2000; Jenkins 1979; Montgomery et al. 2008; Yaffee and McGee 2000).

ARIMA models attempt to uncover the stochastic mechanisms that generate a historical data series. These processes are measured using the patterns observed in the data series; these measurements form the basis for developing population projections. ARIMA models focus on the processes of autoregression, moving average, and differencing.

The autoregressive process has a memory in the sense that it is based on the correlation of each observation with all preceding observations. The impact of earlier observations is assumed to diminish exponentially over time. The number of preceding observations incorporated into the model determines its "order." For example, in a first-order autoregressive process, the current observation is explicitly a function only of the immediately preceding observation. However, the immediately preceding observation is a function of the one before it, which is a function of the one before it, and so forth. Consequently, all preceding observations influence current observations, albeit with a declining impact. In a second-order autoregressive process, the current observation is explicitly a function of the two immediately preceding observations; again, all preceding observations have an indirect impact.

The moving average process attempts to account for "shocks" to the system (i.e., events that have a substantial but short-lived impact on time series patterns). The order of the moving average process defines the number of time periods affected by a given event.

A stationary time series (i.e., one with constant differences over time) is needed to properly construct an ARIMA model. The differencing process is used to achieve such a series. First-order differences (i.e., an observation minus its preceding value) are usually sufficient, but second-order differences (i.e., differences between differences) have been found to be useful for population projections (McNown and Rogers 1989; Saboia 1974; Tayman et al. 2007). Logarithmic and square root transformations may also be useful for stabilizing the variance of a time series.

The most general ARIMA model is expressed as ARIMA (*p, d, q*), where *p* is the order of the autoregressive term, *d* is the degree of differencing, and *q* is the order of the moving average term. (ARIMA models based on time intervals of less than 1 year may also require seasonal terms for *p*, *d*, and *q*). The first step in developing an ARIMA model is to identify the best values for *p*, *d*, and *q*, which typically range from 0 to 2; it is uncommon that $p + q > 3$ in ARIMA models of population and other demographic variables (Alho and Spencer 2005, p. 207). The *d* value is determined first because a stationary series is required to properly identify the autoregressive and moving average processes (Box and Jenkins 1976, p. 174; Granger 1989, p. 72).

A time series should contain enough observations for model identification and parameter estimation. Convention suggests that a minimum of 50 observations is needed for ARIMA modeling (McCleary and Hay 1980, p. 20; Meyler et al. 1998; Saboia 1974), but there is no hard-and-fast rule. Some analysts believe 60 observations are needed; others believe 30 will suffice (Yaffee and McGee 2000, p. 4). Several applications have used fewer than 15 observations, apparently with reasonable success (Campbell 1996; Voss and Kale 1985).

The traditional approach for identifying the best values for *p*, *d,* and *q* focuses on assessing the patterns of the autocorrelation function (ACF) and partial autocorrelation function (PACF) (Box and Jenkins 1976, Chap. 6). This quasi-formal approach to identification is subjective and highly dependent on the skill and interpretation of the analyst (Granger and Newbold 1986, pp. 77–78; Meyler et al. 1998). To help with this problem, more objective methods have been developed such as statistical tests for stationarity (Dickey et al. 1986; Elliot et al. 1996; Phillips and Perron 1988) and statistics such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which can be used to select the best values for *p* and *q* while avoiding a model with too many parameters (Brockwell and Davis 2002, pp. 187–193). It is not unusual to evaluate several tentative models before the best model is selected. An acceptable ARIMA model will have random residuals, no significant values in the ACF and PACF, and the smallest possible values for *p*, *d*, and *q*. The portmanteau test can be used to evaluate the null hypothesis of randomness in a model's residuals (Ljung and Box 1978).

Calculation of population projections from the other complex extrapolation methods requires only the proper value for the time variable and the model's parameters; they are easy to recreate. The formulas used in computing projections from ARIMA models depend on the specification of the values for *p*, *d*, and *q*. Furthermore, projections for a target year may depend on prior projections or a combination of the historical and prior projected values. The temporal sequence of values required will depend on the degree of differencing and the order of the autoregressive and moving average parameters. Developing these projections can be tedious, especially if probabilistic prediction intervals are involved. Fortunately, ARIMA modeling software can be used. Box and Jenkins (1976, pp. 135–138) and Nelson (1973, pp. 144–147) provide details on computing values past the launch year for a wide variety of ARIMA models.

We identified the "best" parameters for p, d, and q using the ACF, PACF, statistical tests, and the AIC and BIC for Franklin County and Grays Harbor County. We used annual observations from 1990 to 2010 to be consistent with the base period used for the other extrapolation methods. Because 21 observations are fewer than is normally recommended for ARIMA modeling, we also examined a larger dataset based on 51 annual observations from 1960 to 2010 (not shown here). We found that the orders of p, d, and q for the best ARIMA models did not change and the projections were fairly close to those based on the shorter data series.

As shown in Fig. 8.1, the time series for Franklin County is not stationary. A non-stationary series will have an autoregressive parameter estimate close to 1.0 and the autocorrelation function will decline very slowly (Nelson 1973, pp. 75–77). Both of these conditions were seen in the population data series for Franklin County. These conditions persisted even after first-order differences were calculated. Second-order differences were examined and their plot over time showed no discernible pattern. The Dickey-Fuller test confirmed that a second-order difference was required to create a stationary series. The patterns of the ACF and PACF and the BIC statistic suggest that Franklin County's historical population followed a first-order autoregressive process with no moving average process. The significant parameter estimate (θ) was 0.376. Checks of the residuals, the ACF, the PACF, and the portmanteau test revealed no problems with the adequacy of the ARIMA (1, 2, 0) model for Franklin County, which included a constant term.

The time series for Grays Harbor County also is not stationary (see Fig. 8.1). A plot of the first-order differences over time showed no discernible pattern and the Dickey-Fuller test confirmed that a first-order difference was required to create a stationary series. The patterns of the ACF and PACF and the BIC statistic suggested that Grays Harbor County's historical population series followed a first-order moving average process with no autoregressive process. The significant parameter estimate (θ) was -0.315. Checks of the residuals, the ACF, the PACF, and the portmanteau test revealed no problems with the adequacy of the ARIMA (0, 1, 1) model, which included a constant term.

Many different ARIMA models can be specified for population projections, reflecting different assumptions that yield different forecasts and prediction intervals (Cohen 1986; Keilman et al. 2002; Lee 1974; Sanderson 1995; Tayman et al. 2007). For example, projections from an ARIMA model with a second-order difference and a constant term tend to follow a non-linear trajectory reflecting a quadratic trend, whereas projections from an ARIMA model with a first-order difference and a constant term tend to follow a linear growth trajectory.

The population projections for Franklin County from the ARIMA (1, 2, 0) model are closest to those from the complex quadratic method and exceed those from the other trend extrapolation methods that assume non-linear population change (see Table 8.7). The non-linear trend in the Franklin County projection is evident from Fig. 8.3. The population grows by 3,200 during the first year of the projection horizon (2010–2011) and annual increases climb steadily thereafter, reaching 5,787 by 2039–2040.

The projections for Grays Harbor County from the ARIMA (0, 1, 1) model are almost identical to projections from the simple LINE method and are similar to those

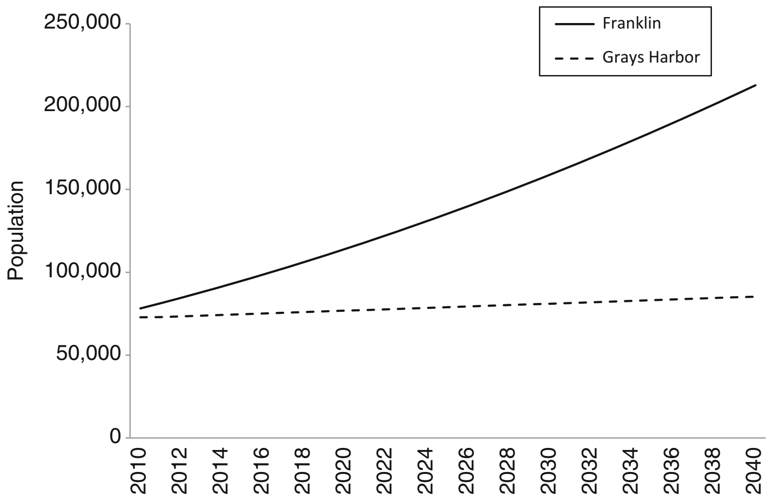

Fig. 8.3 Total population projections: ARIMA model, Franklin and Grays Harbor Counties, 2010–2040 (Projections based on an ARIMA (1,2,0) model for Franklin County and an ARIMA (0,1,1) model for Grey's Harbor County)

from the complex linear trend method (see Table 8.7). The linear trend in the Grays Harbor County projection is evident from Fig. 8.3. One characteristic of a linear ARIMA model is that projections will eventually reach and maintain a constant numeric difference similar to the mean of the historical series (Land 1986; McCleary and Hay 1980, p. 213). The population of Grays Harbor County grows by 209 during the first year of the projection horizon. Annual increases climb to 425 by 2013–2014 but remain constant thereafter. To put these numbers in perspective, the average annual change in the county's population between 1990 and 2010 was 431.

The presence or absence of first-order auto-regressive and moving average terms does not have much impact on forecasts from linear ARIMA models (Alho 1990; Tayman et al. 2007; Voss et al. 1981). For example, the population projections for 2040 for Grays Harbor County from ARIMA (1, 1, 0) and ARIMA (0, 1, 1) models are virtually identical.

8.3 Ratio Methods

Ratio methods express the population of a smaller area (or group) as a proportion of the population of a larger area (or group). For example, a county's population can be expressed as a proportion of a state's population and the number of Hispanics in a county can be expressed as a proportion of the total population of the county. Ratio methods are mostly used where there is a perfect hierarchical structure; that is, where the smaller units are mutually exclusive and exhaustive and can be

Table 8.3 Population projections: Constant-share method, Franklin and Grays Harbor Counties and balance of state, 2015

	2010			2010–2015 change	
	Population	Share	2015 Projection[a]	Number	Percent
Franklin County	78,163	0.01162	81,598	3,435	4.4
Grays Harbor County	72,797	0.01083	76,050	3,253	4.5
Balance of state	6,573,580	0.97755	6,864,552	290,972	4.4
Total	6,724,540	1.00000	7,022,200[b]	297,660	4.4

[a]2010 share × 2015 State projection
[b]Forecast of the State Population, Nov. 2011 Forecast. Washington State OFM Forecasting Division

aggregated to equal the larger unit. For example, census blocks can be aggregated successively into block groups, census tracts, counties, states, and the nation.

Similar to simple extrapolation methods, ratio methods have small data requirements and are easy to apply. In addition, these methods can be constructed so that the sum of the projections for the smaller units equals the projection for the larger unit. We discuss three commonly used ratio methods: (1) constant-share, (2) shift-share, and (3) share-of-growth. Ratio methods require an independent projection of the population of the larger unit, which for most examples in this chapter is the State of Washington. These projections are 7,022,200 for 2015, 7,411,977 for 2020, 8,154,193 for 2030, and 8,790,981 for 2040 (State of Washington 2011). We also use the shift-share method to produce a projection by race/ethnicity for the City of Oceanside, California, where the projection of the total population is 214,530 in 2040 (San Diego Association of Governments 2011).

8.3.1 Constant-Share

In the constant-share method (CONSTANT), the smaller unit's share of the larger unit's population is held constant at a level observed during the base period. Typically, it is the share observed in the launch year. A projection for the smaller unit is made by applying this share to an independent projection of the larger unit's population (shown in bold):

$$\mathrm{P_{it}} = (\mathrm{P_{il}}/\mathbf{P_l})\,(\mathbf{P_t})$$

where P_{it} is the projection for the smaller unit i in target year t; P_{il} is the population of the smaller unit in the launch year; $\boldsymbol{P_l}$ is the population of the larger unit in the launch year; and $\boldsymbol{P_t}$ is the projection for the larger unit in the target year.

The 2015 projections for Franklin County, Grays Harbor County, and the remainder of the State using the CONSTANT method are shown in Table 8.3. In this example, we held shares constant at 2010 launch year values, but shares for any previous point in time (or an average of previous shares) could also be used. The CONSTANT method requires data from only one point in time, making it particularly useful for areas where changing geographic boundaries, poor records, and/or

Table 8.4 Population projections: Shift-share method, Franklin and Grays Harbor Counties and balance of state, 2015

	1990		2010		Change in share	
	Population	Share	Population	Share	1990–2010	2010–2015[a]
Franklin County	37,473	0.00770	78,163	0.01162	0.00392	0.00098
Grays Harbor County	64,175	0.01319	72,797	0.01083	−0.00236	−0.00059
Balance of state	4,765,044	0.97911	6,573,580	0.97755	−0.00156	−0.00039
Total	4,866,692	1.00000	6,724,540	1.00000	0.00000	0.00000
	2015		2010–2015 change			
	Share[b]	Projection[c]	Number	Percent		
Franklin County	0.01260	88,480	10,317	13.2		
Grays Harbor County	0.01024	71,907	−890	−1.2		
Balance of state	0.97716	6,861,813	288,233	4.4		
Total	1.00000	7,022,200[d]	297,660	4.4		

[a]0.25 × 1990–2010 change in share
[b]2010 share + 2010–2015 change in share
[c]2015 share × 2015 State projection
[d]Forecast of the State Population, Nov. 2011 Forecast. Washington State OFM, Forecasting Division

inadequate production time make it impossible to construct a reliable historical data series. Another beneficial attribute of this method is that projections for all the smaller units add to the projection for the larger unit. The main drawback, of course, is that it treats all smaller units exactly the same; that is, it assumes that the populations of all smaller units will grow at the same rate as the larger unit's population. In many instances, this will not be a reasonable assumption.

8.3.2 Shift-Share

In contrast to the constant-share method, the shift-share (SHIFT) method accounts for changes in population shares over time. Different approaches can be used for extrapolating the historical trend in the shares (Gabbour 1993). We describe a shift-share method that assumes a linear trend in shares over the projection horizon:

$$P_{it} = (\mathbf{P}_t)\,\{(P_{il}/\mathbf{P}_l) + [(z/y)\,((P_{il}/\mathbf{P}_l) - (P_{ib}/\mathbf{P}_b))]\}$$

where i denotes the smaller unit; $\boldsymbol{P}$ is the larger unit; z is the number of years in the projection horizon; y is the number of years in the base period; and b, l, and t refer to the base, launch, and target years. The z/y term implements the linear trend and relates the length of the base period to the length of the projection horizon. For example, a projection with a 20-year base period and a 5-year horizon would add 0.25 (i.e., 5/20) times the historical change in population share to the share in the launch year and a projection with a 20-year base period and a 25-year horizon would add 1.25 (i.e., 25/20) times the historical change to the share in the launch year. The 2015 projections for Franklin County, Grays Harbor County, and the remainder of the state using the SHIFT method are shown in Table 8.4.

Table 8.5 Population projections by ethnic group: Shift-share method, City of Oceanside, 2040

	Shares			2040		2010–2040 change	
Ethnic Group	2000	2010	Change	Share[a]	Population[b]	Number	Percent
Non-Hispanic White	0.53599	0.48388	−0.05211	0.32755	70,269	−10,580	−13.1
Non-Hispanic Other	0.16164	0.15734	−0.00430	0.14444	30,987	4,697	17.9
Hispanic	0.30237	0.35878	0.05641	0.52801	113,274	53,327	89.0
Total	1.00000	1.00000	0.00000	1.00000	214,530[c]	47,444	28.4

[a]2010 share + (3 × 2000–2010 change in share)
[b]2040 share × 2040 Oceanside total population projection
[c]2050 Forecast, San Diego Association of Governments, Oct. 2011

Ratio methods can also be used to project demographic subgroups. Table 8.5 illustrates the use of the SHIFT method to project the 2040 population by race/ ethnicity for the City of Oceanside, California. This example uses a 10-year base period from 2000 to 2010. The length the projection horizon is 30 years, meaning that the change in shares between 2000 and 2010 is projected to triple by the year 2040. In this example, the Hispanic share of the population is projected to increase over the projection horizon while the shares of the other two groups are projected to decline.

An important problem inherent in the SHIFT method is that it can lead to substantial population losses in areas that grew very slowly (or declined) during the base period. This problem is more acute when projections cover relatively long horizons (e.g., 20 or more years). For example, in 2040 the population projections for Franklin County and Grays Harbor County are 153,852 and 64,086 (see Table 8.7). Are these projections reasonable? Perhaps for Franklin County, but probably not for Grays Harbor County. SHIFT can even lead to negative numbers, which obviously is not a reasonable projection. This problem can be dealt with by incorporating constraints on projected population shares or on the projected rates of change in those shares. The SHIFT method must be used cautiously for long-range projections, especially for places whose population shares have been declining.

8.3.3 Share-of-Growth

The third ratio method focuses on shares of population *change* rather than population *size*. In this method (SHARE), it is assumed that the smaller unit's share of the population change occurring in the larger unit will be the same over the projection horizon as it was during the base period. This method is sometimes called the *apportionment method* (Pittenger 1976, pp. 89–101; White 1954). Using the SHARE method, the projection of a smaller unit is:

$$\mathrm{P_{it}} = \mathrm{P_{il}} + \{[(\mathrm{P_{il}} - \mathrm{P_{ib}})/(\mathbf{P}_\mathrm{l} - \mathbf{P}_\mathrm{b})]\ (\mathbf{P}_\mathrm{t} - \mathbf{P}_\mathrm{l})\}$$

where the components are defined as shown for the SHIFT method.

Table 8.6 Population projections: Share-of-growth method, Franklin and Grays Harbor Counties and balance of state, 2015

	1990–2010 change		Population		2010–2015 change	
	Number	Share	2010	2015[a]	Number[b]	Percent
Franklin County	40,690	0.02190	78,163	84,682	6,519	8.3
Grays Harbor County	8,622	0.00464	72,797	74,178	1,381	1.9
Balance of state	1,808,536	0.97346	6,573,580	6,863,340	289,760	4.4
Total	1,857,848	1.00000	6,724,540	7,022,200	297,660[c]	4.4

[a]Population 2010 + population change 2010–2015
[b]Share of pop change 1990–2010 × State pop change 2010–2015
[c]Forecast of the State Population, Nov. 2011 Forecast. Washington State OFM, Forecasting Division

The 2015 projections for Franklin County, Grays Harbor County, and the remainder of the state using the SHARE method are shown in Table 8.6. In many instances, this method seems to provide more reasonable projections than either the CONSTANT or SHIFT methods. However, SHARE runs into problems when population change in the smaller unit has the opposite sign of change in the larger unit. For example, suppose that the population of the larger unit grew by 3,000 over the base period and the population of the smaller unit declined by 750; the smaller unit's share of population change would be computed as −750/3,000, or −0.25. If the larger unit were projected to grow by 5,000 over the projection horizon, the smaller unit would be projected to decline by 1,250. This is probably not a reasonable result. If anything, the smaller unit is likely to decline by a smaller amount (or even increase a bit) because the larger unit is projected to have more population growth in the future than in the past.

In situations such as these, the SHARE method should not be used in the manner just described. Rather it must be adjusted in some way, such as by using a variant of the plus-minus method described in Chap. 10. Some applications of this method simply project zero change for the smaller unit when its change is in the opposite direction of change in the larger unit (Pittenger 1976, p. 101).

8.3.4 Other Applications of Ratio Methods

The ratio methods described and illustrated in this chapter were used solely for population projections, but they have many other applications in demography. Some of these are discussed in Chaps. 4 and 5, where we describe the use of ratios for relating projections of mortality or fertility rates in one area to rates projected for another area. In Chap. 9, we describe a simple application of structural models based on ratios.

In addition, ratios are frequently used in combination with population projections to develop projections of other variables or demographic characteristics.

For example, projections of households can be made by applying projected "householder" rates by age and sex to population projections by age and sex. Householder rates are simply ratios of the number of householders to the number of persons, calculated for each age-sex group. Similarly, projections of the labor force can be made by applying projected labor force participation rates by age and sex to population projections by age and sex (race and ethnicity can also be used). Labor force participation rates are simply ratios of the number of persons in the labor force to the total number of persons, calculated for each age-sex group. Projections of school enrollment, persons with disabilities, and many other variables can be made following similar procedures. We explore some of these applications in Chap. 11.

8.4 Analyzing Projection Results

Using the 11 extrapolation methods and the 20-year base period from 1990 to 2010, we projected the total population of Franklin County and Grays Harbor County for the years 2020, 2030, and 2040 (see Table 8.7). What can these projections tell us?

Most of the projections for Grays Harbor County are similar. Except for the polynomial model and two of the three ratio methods, all the projections for 2040 fall between 82,366 and 89,781. This is a common result. When they have the same base period and launch year, projections for areas with slow or moderate growth rates often fall within a fairly narrow range. This outcome is found not only for trend extrapolation methods but—as we show in Chap. 13—for most other projection methods as well.

The reasons for the three exceptions are clear. Projections based on the polynomial model were influenced by the quadratic term, which translates into relatively large population increases. CONSTANT yields relatively high projections because it assumes that the population of Grays Harbor County will grow at the same rate as the state as a whole, whereas it grew much more slowly during the base period. SHIFT assumes that Grays Harbor County's share of the state population will continue to decline; these steadily declining shares lead to a steadily declining population. CONSTANT and SHIFT will generally produce results that are quite different from other trend extrapolation methods whenever population growth in the smaller unit differs substantially from growth in the larger unit.

Projections for Franklin County show much more variation among methods than projections for Grays Harbor County. Projections based on non-linear models (GEO, EXPO, quadratic, exponential, logistic) are decidedly higher than those based on linear models (LINE, linear). Projections from the ARIMA model fall in between, as the effect of compound growth rates is muted because of the first-order auto-regressive term; a model with a higher-order autoregressive term would have created a more explosive growth trajectory

Table 8.7 Population projections based on alternative extrapolation methods, Franklin and Grays Harbor Counties, 2020–2040

	Franklin			Grays Harbor		
Extrapolation method	2020	2030	2040	2020	2030	2040
Simple						
LINE	98,508	118,853	139,198	77,108	81,429	85,730
GEO	112,884	163,028	235,446	77,531	82,573	87,942
EXPO	112,888	163,040	235,473	77,531	82,572	87,942
Complex						
Linear	98,444	118,724	139,005	77,536	82,275	87,015
Quadratic	125,619	191,192	274,881	79,940	88,687	99,037
Exponential	114,725	167,154	243,545	78,039	83,641	89,646
Logistic	115,696	171,622	254,950	78,074	83,725	89,781
ARIMA[a]	118,182	158,985	212,828	76,823	81,065	85,307
Ratio						
CONSTANT	86,127	94,752	102,151	80,272	88,310	95,206
SHIFT	100,655	126,716	153,842	71,526	69,066	64,086
SHARE	93,218	109,472	123,418	75,987	79,431	82,386
Projection range						
Numeric difference	39,492	96,440	172,730	8,746	19,621	34,951
Percent difference	46%	102%	169%	12%	28%	55%

[a]Franklin County ARIMA (1,2,0) and Grays Harbor ARIMA (0,1,1); 20-year base period

(Tayman et al. 2007). These results illustrate the impact of applying compounding growth rates in areas that have been growing rapidly. In most instances, this will not be a reasonable assumption (especially for projection horizons longer than 5 or 10 years).

The three ratio methods also show a substantial degree of variation in Franklin County, but SHIFT now produces the highest projections and CONSTANT the lowest, reversing the pattern seen for Grays Harbor County. This result is not surprising, since the population of Franklin County grew much more rapidly than the state's population during the base period, whereas the population of Grays Harbor County grew much more slowly.

Given this degree of variability, how does one decide which trend extrapolation method or methods to use for constructing a set of population projections? One approach is to take an average of projections from several methods. This is the approach followed by the Bureau of Economic and Business Research at the University of Florida in its production of county projections of total population (Smith and Rayer 2012). Using a combination of five extrapolation methods and three base periods, they produced nine projections for each county and calculated three averages, one using all nine projections, one in which the highest and lowest projections were excluded, and one in which the two highest and two lowest were excluded. In most counties the third average was used as the baseline projection. When averaging several projections, one must decide on which methods to include and whether the average should be weighted or unweighted. We discuss these issues in greater detail in Chap. 13.

8.5 Conclusions

Trend extrapolation methods have a long history in demography. In spite of the ascendancy of the cohort-component method and the development of structural and microsimulation models over the last half century, these methods are still commonly used for population projections, especially for small areas. They have a number of useful characteristics, but some serious shortcomings as well.

Simple trend and ratio extrapolation methods have very small data requirements. LINE, GEO, EXPO, SHIFT, and SHARE can be applied using total population data from only *two* points in time. CONSTANT requires data from only *one* point in time. These methods are easy to apply and to explain to data users. They do not require sophisticated modeling or programming skills; in fact, they can be applied rather easily using only a hand calculator. Because of their small data requirements and ease of application, these methods can be applied in a timely manner and for very little cost. They are particularly useful for small areas, where data availability and reliability create substantial problems for more complex or sophisticated methods.

Complex trend extrapolation methods require data from a number of points in time; this requirement prevents the use of these methods in many small areas. Complex extrapolation methods also require greater modeling and statistical skills than simple extrapolation methods, especially for developing logistic and ARIMA time series models. However, compared to cohort-component and structural models, even complex trend extrapolation methods are characterized by low costs, timeliness, and small data requirements. In addition, several of these methods can be used to develop prediction intervals to accompany population forecasts. We return to this point in Chap. 13.

Trend extrapolation methods suffer from several shortcomings. They do not account for differences in demographic composition or for differences in the components of growth. Because they have no theoretical content beyond the structure of the model itself, they cannot be related to behavioral or socioeconomic theories of population growth (the logistic model is an exception). Consequently, they are not useful for analyzing the determinants of population growth or for simulating the effects of changes in particular variables or assumptions. In addition, they can lead to unrealistic or even absurd results if carried too far into the future (see Box 8.1).

The basic assumption underlying trend extrapolation methods is that—in terms of the population change specified by a particular method—the future will be just like the past. Given the changes that have occurred over time, that assumption would seem to be questionable if not completely unrealistic. Just how useful are trend extrapolation methods? How accurate are their projections when used as forecasts? How does their forecast accuracy compare with the accuracy of other commonly used projection methods? We provide some answers to these questions in Chaps. 12 and 13.

Box 8.1 One Man's View of Extrapolation Methods

"In the space of one hundred and seventy-six years the Lower Mississippi has shortened itself two hundred and forty-two miles. That is an average of a trifle over 1 mile and a third per year. Therefore, any calm person, who is not blind or idiotic, can see that in the Old Oolitic Silurian Period, just a million years ago next November, the Lower Mississippi River was upward of one million three hundred thousand miles long, and stuck out over the Gulf of Mexico like a fishing-rod. And by the same token any person can see that seven hundred and forty-two years from now the Lower Mississippi will be only a mile and three-quarters long, and Cairo and New Orleans will have joined their streets together, and be plodding comfortably along under a single mayor and a mutual board of aldermen. There is something fascinating about science. One gets such wholesale returns of conjecture out of such a trifling investment of fact."

Mark Twain, *Life on the Mississippi,* p. 136.

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Chapter 9
Structural and Microsimulation Models

Suppose that a new freeway extending into the sparsely populated outskirts of Denver were built. What impact would that freeway have on the population and housing growth of these outlying areas? Suppose that a large meatpacking plant were built in a small town in Iowa. What impact would the new plant have on the town's population growth and demographic characteristics? Suppose that a large military base in South Carolina were closed as part of a cutback in the federal defense budget. What impact would this base closure have on the population and economy of the county in which the base was located?

Demographers, planners, and other decision makers often face questions like these, but the projection methods described thus far are unable to provide any answers. This is where structural modeling comes into play. Structural models use statistical techniques that base population changes (or—more commonly—changes in a particular component of population growth) on changes in one or more independent (i.e., explanatory) variables. Structural models are invaluable for many planning and policy-making purposes because they explicitly account for the influence of factors such as employment, rents, wage rates, land use, housing, and the transportation system (Johnston and McCoy 2005; Treyz 1995; Zhou et al. 2009).

Structural models can be expressed in many ways. Some focus on total population. For example, population growth for census tracts might be based on the spatial distribution of employment opportunities and housing prices within a county. Others focus on specific components of population growth, such as migration. For example, county migration projections might be based on projected changes in wage rates and employment. When structural models focus on a particular component of population growth, they are generally linked to a cohort-component model in order to complete the projection.

Some structural models are relatively simple, containing only a few variables and equations (Mills and Lubuele 1995). Others are very complex, with huge systems of simultaneous equations involving many variables and parameters (Zandy and Posar 2010). Likewise, the procedures for projecting a model's independent variables range from simple extrapolation and shift-share techniques to

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formal multi-equation statistical models. We do not discuss the procedures for projecting a model's independent variables in this chapter; such descriptions can be found elsewhere (Bolton 1985; Greenberg et al. 1978; Hunt and Abraham 2005; Putman 1991; Treyz 1993).

We discuss two categories of structural models. The first covers *economic-demographic models*, which are typically used to project population and economic activities for counties, labor market areas, metropolitan areas, and states. The second covers *urban systems models*, which are used primarily for projecting population, housing, land use, economic activities, and transportation patterns for census tracts, block groups, blocks, and other small geographic areas. Although economic-demographic and urban systems models are distinguished largely by differences in geographic scale, they typically provide different explanations of the causes and consequences of population change.

For many years, population projections were made primarily at the national and state levels. In recent decades they have been made at progressively lower levels of geography. Taking this trend to its logical conclusion suggests the development of projections for individual households and people. This approach—commonly referred to as *microsimulation*—has become increasingly popular during the last decade and has been used in scientific as well as policy-supporting research in Europe, Australia, Canada, and the United States (Dekkers and Zaidi 2011). Microsimulation models sometimes incorporate only demographic variables, but often incorporate non-demographic variables as well (O'Neill et al. 2001).

Our objective in this chapter is to provide a general introduction to the use of structural and microsimulation models for developing population projections. We do not attempt to provide detailed descriptions of all the processes, techniques, and strategies that can be used to formulate, build, calibrate, test, and implement these models. Such descriptions can be found elsewhere (Gilbert 2008; Jin and Fricker 2008; Pagliara et al. 2010; Putman 1991; Treyz 1993; Troitzsch et al. 2010).

9.1 Structural Models: Economic-Demographic

A properly constructed economic-demographic model is not simply a collection of disparate variables and equations, but represents a distinct theoretical framework postulating a variety of interrelationships among demographic, economic, and other variables. Such models have been widely used for analyzing the determinants and consequences of fertility, mortality, and migration for many years. For purposes of population projection, however, they generally focus on migration. We know of only a few instances in which economic-demographic models have been used for projecting fertility or mortality rates, and then only for projections of large areas such as nations or regions of the world (Ahlburg 1986, 1999; Sanderson 1999). Mortality and fertility models for small areas have been proposed (Isserman 1985), but to our knowledge have not been implemented.

There are several reasons for focusing on migration in projections for states and local areas. First, migration rates are more volatile than mortality and fertility rates, having the potential to change much more rapidly within a short period. Second, migration generally has a greater impact on population change than either births or deaths in areas that are growing or declining rapidly. Third—and perhaps most important for small-area projections—economic fluctuations have a greater impact on migration patterns than on mortality and fertility rates. For these reasons, we confine our discussion to models focusing on migration or changes in total population.

We begin this section by describing several factors that influence state and local migration patterns. We then discuss and illustrate two classes of models in which these factors are used to project migration or total population. Recursive models account for the impact of one or more independent variables on population change, but do not consider the impact of population change on those variables. Non-recursive models, on the other hand, allow for two-way interactions; that is, they consider both the determinants and the consequences of population change.

9.1.1 Factors Affecting Migration

Human capital theory has guided many studies of the determinants of migration (Greenwood 1997; Poot et al. 2009; Sjaastad 1962). According to this theory, migration is an investment in human capital involving both costs and benefits. People migrate if the present value of all future gains in benefits is expected to outweigh the full costs of migration. This theory echoes Ravenstein's words from more than a century ago, that people migrate primarily "to 'better' themselves in material respects" (Ravenstein 1889, p. 286). Narrowly interpreted, this theory implies that people will move to the area in which their economic opportunities are expected to be the greatest.

Economic opportunities are typically measured using variables such as job growth, unemployment rates, wages, and income. In addition to their theoretical relevance, data on these variables are readily available for many geographic areas and points in time. The U.S. Bureau of Economic Analysis (BEA), for example, provides time series data for wages and income for states, counties, and metropolitan areas. The U.S. Bureau of Labor Statistics (BLS) provides historical labor force, employment, and unemployment data for states, metropolitan areas, and many counties.

As noted in Chap. 6, economic factors are not the only ones affecting the decision to migrate. Amenities such as climate, crime rates, and coastal location play a major role (Clark and Murphy 1996; Graves and Linneman 1979; Schachter and Althaus 1989; Zhang 2008). Life cycle changes such as marriage, divorce, childbirth, and retirement are also important, as are personal characteristics such as age, education, income, family ties, and residential preferences (Astone and McLanahan 1994; DaVanzo and Morrison 1978; Fuguitt and Brown 1990; Mincer

1978; Radu 2008). In addition, social networks are known to have an important impact on migration flows to some areas (Anjos and Campos 2010; Massey et al. 1987).

From a theoretical perspective, a complete migration model should include a variety of economic and non-economic variables. Using such a model for migration projections, however, would be very difficult. In addition to the problem of finding reliable historical data, all the independent variables themselves must be projected (Stillwell 2005). Such projections are seldom available, especially for small areas. Since projections of economic variables are more likely to be available than projections of non-economic variables, narrowly economic models have a distinct advantage over theoretically richer formulations for projecting migration.

We discuss three economic factors that influence state and local migration patterns: employment, the unemployment rate, and wages (or income). Although this list is not exhaustive, these variables have a substantial impact on migration and are often included in economic-demographic models. We also discuss the role played by amenities, focusing on two theories of migration that offer opposing views regarding the relative importance of economic factors and amenities as determinants of migration. Understanding the determinants of migration is essential before a valid model can be constructed.

9.1.1.1 Employment

More than 40 years ago, the American Statistical Association suggested that studies of internal migration focus on the relationship between the growth in jobs and the movement of people (American Statistical Association 1977, p. 7). Within the human capital framework, it is assumed that potential migrants perceive areas with increasing employment opportunities to be more attractive than areas with few or declining employment opportunities. It would be expected, then, that areas with relatively high (low) rates of job growth would have relatively high (low) rates of population growth due to migration.

This expectation is strongly supported in the empirical literature. Studies using a variety of employment and migration measures have found results consistent with the predictions of economic theory (Ashby 2007; Clark and Hunter 1992; Cutler and Davies 2007; Greenwood 1975; Treyz et al. 1992). Simply put, jobs attract people and people create jobs. This finding forms the foundation of virtually every economic model of migration in use today.

The exact nature of the employment-migration relationship, however, varies over time and among geographic areas (Greenwood 1981, pp. 40–46; Greenwood and Hunt 1984, 1991; Plane 1989). New jobs can be filled not only by new migrants, but also by the local population through a reduction in the unemployment rate, an increase in labor force participation, or changes in commuting patterns (Congdon 1992; Partridge and Rickman 2006). At the extreme, migrants may take all the new jobs in an area or they may not take any; the reality usually lies somewhere in between. These factors—plus the time and money costs of a job search—help explain the lag often seen between employment changes and subsequent population movements (Greenwood 1985).

To clarify the roles of commuting patterns and migration as responses to changes in local employment opportunities, it is useful to view an area in terms of its labor market. A labor market can be defined as the range of employment opportunities available to a worker without changing his or her place of residence (Fischer and Nijkamp 1987). Labor markets often span a number of counties, extend across state lines, and reflect commuting distances of one, two, or even more hours. Workers can respond to new job opportunities not only by migrating (i.e., changing residence), but also by adjusting their daily commuting patterns. For example, many residents in southern Riverside County, California commute more than 150 miles each day (round trip) to jobs in San Diego County. Similar examples can be found in labor markets throughout the United States.

Human capital theory suggests that in-migration should be positively related to changes in job opportunities. This expectation has been strongly supported in the empirical literature. It might also be expected that out-migration would be inversely related to changes in job opportunities. That is, when the economy is strong and employment is growing, fewer persons would be expected to leave the area in search of employment elsewhere. Conversely, when the economy is weak and employment is stagnant or declining, more people would be expected to leave the area to seek jobs elsewhere.

The empirical evidence for out-migration is not nearly as strong as it is for in-migration. The relationship between employment and out-migration has often been found to be non-linear and weaker than the relationship between employment and in-migration (Kriesberg and Vining 1978; Plane et al. 1984). Some studies (Greenwood 1975; Schachter and Althaus 1989) have found the expected negative relationship, but others have found a positive relationship between in- and out-migration; that is, places with high (low) levels of in-migration also have high (low) levels of out-migration (Meuser and White 1989; Plane 1989; Stone 1971). Why might this be true? One explanation is that areas with large numbers of in-migrants have populations that are relatively migration-prone, thereby raising the likelihood of out-migration. Another explanation is that in-migration creates its own counter-stream, as in-migrants return to their previous places of residence. Whatever the explanation, the empirical evidence provides a stronger basis for projecting in-migration than out-migration.

The overall strength of the employment-migration relationship, however, implies that measures of employment are likely to be useful in structural models of migration. In fact, the employment-migration relationship forms the basis of most of the structural models in use today.

9.1.1.2 Unemployment Rate

The unemployment rate is a widely watched measure of the economy, as evidenced by the emphasis attached to the unemployment figures released each month by the

BLS. In general, a high unemployment rate is a sign that the economy is not creating enough jobs for those wanting to work. Conversely, a low unemployment rate is a sign of a "healthy" economy creating jobs for most of those wanting to work. In the human capital framework, migrants perceive areas with low unemployment rates as attractive and areas with high unemployment rates as unattractive. Areas with rising unemployment rates would therefore be expected to have increasing levels of out-migration and declining levels of in-migration, while areas with falling unemployment rates would be expected to have increasing levels of in-migration and declining levels of out-migration.

Despite the theoretical rationale and the findings of a few studies (Foot and Milne 1989; Hamalainen and Bockerman 2004; Haurin and Haurin 1988), much empirical research on this topic has found unexpected signs or insignificant effects (Clark and Hunter 1992; Gallin 2004; Greenwood 1975, 1985; Schachter and Althaus 1989). What might explain these poor empirical results? Gordon (1985) believes the rate of employment growth is more important to potential migrants than the unemployment rate, swamping its observed effect. Haurin and Haurin (1988) believe that employment and wage variables have been improperly included in migration equations, minimizing the true impact of the unemployment rate. Another explanation is based on the statistical issue of simultaneity: when the unemployment rate is measured at the end of the migration period, it not only influences migration but is also influenced by migration (Greenwood 1981).

The relatively small size of the unemployed population also may be a factor, masking the true relationship between the unemployment rate and migration. Since high unemployment rates are likely to be of more concern to the unemployed than the employed, the effects of unemployment on migration may not be apparent in studies using aggregate data (Greenwood 1985). Consequently, unemployment effects may be more evident in studies using micro data than studies using aggregate data. For example, DaVanzo (1978) analyzed survey data for individuals and found the unemployed to be more likely to move than jobholders. She concluded that higher unemployment rates did indeed encourage out-migration. Several studies have supported DaVanzo's findings, but others have failed to confirm them (Greenwood 1997).

The empirical evidence on the unemployment-migration relationship is somewhat murky. Some studies have found significant effects with the expected signs, but others have found no significant effects or even effects with the wrong signs. Based on this evidence, we believe that unemployment rates will generally not perform as well as other economic variables in structural models used for projecting migration.

9.1.1.3 Wages and Income

The human capital model suggests that wages (or income) should be positively associated with in-migration and negatively associated with out-migration. Areas with relatively high wages or incomes would therefore be expected to attract a relatively large number of in-migrants and lose a relatively small number of out-migrants, while areas with relatively low wages or incomes would be expected to attract relatively few in-migrants and lose a relatively large number of out-migrants.

General support for these expectations is found in the literature (Foot and Milne 1989; Gallin 2004; Schachter and Althaus 1989; Treyz et al. 1992). However, the strength of this effect—although greater than for the unemployment rate—is not as great as it is for measures of job growth (Greenwood 1981; Isserman et al. 1985).

Several explanations have been offered for the relatively weak influence of wages (or income) on migration. Household data have shown that wages are not always the most prominent factor in a person's motivation for moving, especially for people in older age groups (Gibbs 1994; Long and Hansen 1979). Isserman et al. (1985) noted that capital may be attracted to low-wage regions, thereby raising employment opportunities and attracting in-migrants; this "employment effect" might obscure the relationship between wages and migration. Vijverberg (1993) suggested that higher wages might actually discourage migration because of diminishing marginal returns to income. Krieg and Bohara (1999) found that using aggregate earnings data obscures the effect of wages on migration because unmeasured personal characteristics such as ambition, drive, and the quality of schooling—which have a positive impact on migration—are not picked up in the data. Simultaneity bias has also been suggested as a possible explanation for the lack of a clear relationship between income and migration (Sjaastad 1960), but this explanation has not been supported in several studies using two- and three-stage least squares estimation techniques (Greenwood 1975, 1981).

The empirical evidence on the relationship between migration and wages (or income) is generally consistent with the predictions of human capital theory, but is not particularly strong. Wage (or income) data have been used successfully in a number of projection models, but do not play as large a role as employment as a determinant of migration.

9.1.1.4 Amenities

The discussion thus far has focused on economic determinants of migration. However, people also consider a variety of other factors when making migration decisions. We use the term *amenities* to describe the non-economic characteristics of an area, such as climate, topographical features, cultural attractions, recreational opportunities, air quality, and crime rates. Because amenities have a substantial impact on the quality of life in an area, it would be expected that they would also have an impact on migration patterns. How important are amenities compared to economic factors as determinants of migration? This question has given rise to two competing theories of migration.

Before the 1970s, most migration research focused on regional differences in economic variables such as wages, employment, and income. This research was based on the assumption that the economic system was in a constant state of disequilibrium, as reflected by the existence of persistent geographic differences in economic opportunities. Migration thus acts as an "equilibrating mechanism" shifting people from one area to another, thereby reducing these differences over time. Geographic differences in economic opportunities tend to persist, however, because the labor market is slow to adjust to changes. Although disequilibrium theorists acknowledge that geographic differences in amenities may affect migration, they believe differences in economic opportunities are the main explanatory factors (Hunt 1993; Sjaastad 1962).

An alternative theory has gained adherents over the last few decades, in part because of the failure of economic variables to provide consistent explanations of migration in empirical studies (Greenwood 1997). Equilibrium theory postulates that differences in amenities—rather than differences in economic opportunities—are the main determinants of migration (Clark et al. 2003; Graves 1983; Graves and Linneman 1979; Krupka 2009). Equilibrium theorists assume that labor markets, land markets, and the migration process itself are efficient. Consequently, migration quickly eliminates any significant geographic differences in economic opportunities and promptly restores equilibrium (Graves and Knapp 1988; Schachter and Althaus 1989). Observed regional differences in wages or income are simply compensating for regional differences in amenities. Equilibrium theorists also believe that failing to account for amenities in migration equations can lead to model misspecification and biased parameter estimates (Graves 1980).

The empirical evidence related to this debate is mixed. Some studies have found support for the predictions of equilibrium theory (Clark and Murphy 1996; Graves and Mueser 1993; Rickman and Rickman 2011; Schachter and Althaus 1989) while others have found support for the predictions of disequilibrium theory (Carlino and Mills 1987; Greenwood et al. 1986; Greenwood and Hunt 1989) or cast doubt on the equilibrium perspective (Evans 1990; Henderson 1982; Hunt 1993; Treyz et al. 1993).

A substantial amount of empirical evidence shows that both economic opportunities and amenities influence migration, and that including both types of variables generally improves migration modeling (Greenwood et al. 1991; Partridge and Rickman 2006). The life cycle literature further suggests that economic variables are more important to working-age people and that amenity variables become more important as people become older (Clark and Hunter 1992). We believe both types of variables have important effects on migration, but structural models used for population projections generally focus primarily on economic factors. Consequently, our discussion of structural models focuses on the economic determinants of migration.

9.1.2 Recursive Models

Recursive models are based on one-way interactions: independent variables influence dependent variables but dependent variables do not influence independent variables. In recursive models, the basic assumption is that the economic factors affecting migration are themselves unaffected by migration. Is this a reasonable assumption? Probably not. Over time, migration has a direct impact on job growth, wages, unemployment rates, and a host of other economic and non-economic variables. From a theoretical perspective, then, recursive models do not reflect the full range of interactions between migration and the economy.

Recursive models do, however, pick up a number of important effects and are simpler to develop and easier to apply than models that account for two-way interactions. Consequently, they are well represented in the literature and in practice. Recursive models have been developed for explaining and projecting net migration flows (Clark and Hunter 1992; Greenwood et al. 1986, 1991; Greenwood and Hunt 1991; Haurin and Haurin 1988) and gross migration flows (Ashby 2007; Greenwood 1975; Schachter and Althaus 1989). Recursive relationships have also been incorporated into several multi-regional migration models (Campbell 1996; Foot and Milne 1989; Isserman et al. 1985; Rogers and Williams 1986).

We discuss three general approaches to designing and implementing recursive models. First, we look at models using regression analysis to project migration as a direct statistical function of a set of economic variables; following conventional practice, we refer to these as *econometric models*. Second, we examine an approach that treats migration as a balancing factor, adjusting for differences between the projected supply and demand for labor. Finally, we discuss a method that uses population/employment ratios to derive population projections from employment projections.

9.1.2.1 Econometric Models

Under the econometric approach, equations are developed in which migration is determined by one or more independent variables, such as those discussed in the previous section. Using historical data and regression techniques, parameters are estimated for each independent variable. Migration projections are made by applying the parameter estimates to projections of the independent variables. The migration equations are typically integrated into a larger structural model providing projections of the entire economy.

Parameter estimates are typically based on time series data measured at annual intervals. Since the equations are recursive, they can usually be estimated using ordinary least squares (OLS) regression techniques. The presence of autocorrelation—a likely possibility with time series data—may require more complicated techniques such as those described by Cochrane and Orcutt (1949) and Bates and Watts (1988, pp. 92–96).

Another common practice is to use non-linear transformations such as the natural logarithm (Stock and Watson 2010, Chap. 8). Non-linear transformations not only help correct statistical problems such as non-normality in the regression residuals, but also may provide a better description of the relationship between the independent variables and migration. A crucial assumption in most econometric projection models is that parameters and functional forms do not change over the projection horizon. In other words, it is assumed that the historical relationships between migration and the independent variables remain constant over time.

Net migration models require the estimation of a single migration equation (unless net migration is divided into several categories to account for differences in demographic characteristics, such as age). Simple gross migration models require the estimation of two equations, one for in-migrants and one for out-migrants. Regardless of the approach, the model-builder attempts to construct equations that accurately portray the influence of the independent variables on migration. Variables such as changes in employment and wage rates are typically used to measure area-specific economic conditions. A potentially useful strategy is to define economic conditions for one area in relation to those found in another area, most often the nation. This approach provides a mechanism for capturing the effects of national economic trends on the local economy (Freeman 2001; Greenwood 1981; Treyz et al. 1993). Furthermore, by focusing on relative rather than absolute changes in economic conditions, this strategy is consistent with human capital theory's emphasis on comparisons of economic conditions in different geographic areas.

Multi-regional models require the most data because they incorporate specific place-to-place migration flows. For example, a state-to-state model (including the District of Columbia) involves 2,550 gross migration flows (51 by 50). In comparison, a net migration model for states requires only 51 migration flows and a two-region gross migration model requires only 102. Large data requirements present a formidable challenge in the construction of multi-regional models.

Isserman et al. (1985) developed a Markov transition model using annual IRS data to project multi-state migration flows. They constructed a transition matrix reflecting the probability that a person will migrate from one state to another (or remain in the same state). This model incorporated the size and characteristics of the origin population, changes in economic conditions at all potential destinations, and base year migration probabilities by origin and destination. The authors constructed an economic attractiveness index based on the ratio of employment growth to unemployed workers as a measure of economic conditions. They used empirically-based parameter estimates to measure the impact of changes in the attractiveness index on migration.

Gravity models represent another approach to modeling multi-regional migration flows. In a gravity model, a migration flow is directly related to the size of the origin and destination populations and inversely related to the distance between the two areas. These models can be adjusted to include other determinants of migration as well. Foot and Milne (1989), Rogers (1967), and Yano et al. (2003) provide examples of gravity models incorporating economic factors. We discuss gravity models in more detail later in this chapter.

9.1.2.2 Balancing Labor Supply and Demand

Another widely used recursive model matches independently derived projections of labor supply and labor demand to determine migration. If supply exceeds demand, workers are projected to move out of the area; if demand exceeds supply, workers are projected to move in. In both cases migration tends to restore the balance between labor supply and demand. We refer to this as a *balancing model*.

A balancing model is a two-part model in which labor supply is determined using a traditional cohort-component model (with one important difference discussed below) and labor demand is determined by economic factors. Such a model is typically used to project only the migrants most affected by changes in employment opportunities; other migrants must be projected using other techniques. Unlike an econometric forecasting model, a balancing model does not require formal statistical equations or time series data to project future levels of migration. In addition, it does not require the implementation of a large-scale model of the economy. Consequently, balancing models are less costly to implement and easier to use than econometric models and are more accessible to a wider range of practitioners.

We present a brief overview of the steps involved in developing and implementing a balancing model. Actually applying the model, however, requires detailed computations and the specification of a number of assumptions. Murdock and Ellis (1991, pp. 221–222) provide a simple numerical example illustrating the use of a balancing model for population projections.

The first step is to project the demand for labor, which is usually represented by some measure of employment opportunities (e.g., the total number of jobs). It is typically projected using export-base models, input-output models, or shift-share techniques (Greenberg et al. 1978; Miller and Blair 2009; Murdock et al. 1984). In some instances, projections of labor demand are based on large-scale econometric models (Reeve and Perlich 1995).

The second step is to project the supply of labor. This usually involves a cohort-component model in which mortality and fertility rates are applied in the usual manner, but migration rates are assumed to be zero; in other words, the population is "closed" to migration. Labor force participation (LFP) rates are projected by assuming that current rates will remain constant, that local rates will follow national trends, or that some other trend will prevail. The BLS provides national projections of LFP rates by age, sex, race, and Hispanic origin (Toossi 2012). Labor supply is then projected by multiplying the projected population by the appropriate LFP rates. Although labor supply can be projected using LFP rates based on the total population, it is more common to use rates broken down by age, sex, race, and other demographic characteristics.

The third step is to derive the migration projection by matching labor supply and labor demand. This can be done using a variety of procedures ranging from relatively simple to relatively complex (Murdock and Ellis 1991, p. 219). For example, Murdock et al. (1984) developed a model specifying four types of labor demand and labor supply broken into age-sex groups. Murdock et al. (1987) describe this model in detail. In the simplest model, the volume of net migration is equal to the gap between labor supply and demand. Net in-migration occurs when labor demand is greater than labor supply and net out-migration occurs when labor supply is greater than labor demand. This assumption can be relaxed by setting thresholds that trigger the migration response; that is, it can be assumed that migration will not occur until labor supply and labor demand are out of balance by more than some predetermined amount (Murdock et al. 1984).

The matching procedure in the third step determines the net number of workers that leave or enter the area. The fourth step converts these migrating workers into a projection of all "economic" migrants, including other family members, by applying various characteristics to the migrating workers (e.g., marital status and family size). The assumptions made for these characteristics can markedly influence the size of the migrant population and require careful attention (Murdock and Ellis 1991, p. 220).

The economic migrants projected in the fourth step do not represent all migrants; in particular, they exclude groups such as retirees, military personnel, and international migrants whose moves are largely unaffected by changes in local economic conditions. The fifth step projects these groups using procedures such as those described in Chap. 7. Adding these migrants to those projected in Step 4 completes the migration projection.

A final step ascribes demographic characteristics to the migrants. This can be done in a number of ways. One commonly used procedure is to give migrants the same characteristics as the U.S. population when net migration for an area is positive and the same characteristics as the local population when net migration is negative (Center for the Continuing Study of the California Economy 2010).

9.1.2.3 Population/Employment Ratios

Our final recursive model does not single out migration or any other individual component of population change. Rather, it develops population projections from employment projections and the projected ratio of population to employment (P/E). In its simplest form, this model uses projections of total employment and holds the P/E ratio constant at its most recent value. However, since P/E ratios are known to vary by demographic characteristic and to change over time, this simple approach is not commonly used (Murdock and Ellis 1991, p. 217). More refined approaches can be followed, such as projecting trends in P/E ratios or segmenting projections into person of working ages (e.g., 18–64), retirement ages (e.g., 65+), and young dependent ages (e.g., <18) (U.S. Bureau of Economic Analysis 1995). Despite some drawbacks, this approach offers an easy and inexpensive way to derive population projections from economic projections.

9.1.3 Non-Recursive Models

Recursive projection models have been criticized on both statistical and theoretical grounds because they view economic-demographic relationships as one-sided: They account for the influence of economic factors on population growth, but do not account for the influence of population growth on economic conditions. However, a large body of evidence shows that demographic variables are not only affected by economic variables, but influence those variables as well (Muth 1971; Partridge and Rickman 2003; Plane 1993). Non-recursive models address this problem by incorporating relationships that simultaneously depict both the economic determinants and consequences of demographic change. Although they have more complicated mathematical structures and larger resource requirements than recursive models, a number of non-recursive projection models have been developed and implemented (Conway 2001; Mills and Lubuele 1995; Treyz and Treyz 2004).

We have explained how economic factors—especially changes in employment—affect migration and population growth. Almost 50 years ago, Borts and Stein (1964) argued that the opposite is also true: Migration is not only influenced by changes in employment, but influences employment as well. They based their argument on the premise that an area's labor demand curve is perfectly elastic; therefore, employment will increase by the same amount as the shift in the labor supply curve. Since labor supply is affected by migration, employment must be affected by migration as well.

A fundamental question has been posed: Do people follow jobs or do jobs follow people? In a groundbreaking study, Muth (1971) found support for both views, but concluded that the evidence more strongly favored the Borts and Stein hypothesis. Specifically, Muth estimated that every 10 new jobs attract between six and seven new migrants, but every 10 new migrants create 10 additional jobs. Steinnes (1982) concluded that causality runs only one way, from change in residence to change in manufacturing employment. His study rekindled the causality debate.

Greenwood et al. (1986) found that migrants fill about five out of every 10 new jobs, a bit lower than Muth's estimate. Turning to migration's impact on employment, they estimated an effect about 36% higher than Muth's. Similarly, Clark and Murphy (1996) and Mills and Lubuele (1995) found stronger support for the hypothesis that jobs follow people than for the hypothesis that people follow jobs. Carlino and Mills (1987), Freeman (2001), and Mathur and Song (2000), however, found the impact of employment growth on population growth to be greater than the impact of population growth on employment growth. Partridge and Rickman (2003) found that people follow jobs and jobs follow people, but that the impacts were similar in both directions.

Although these studies reached different conclusions regarding the magnitude and significance of various economic-demographic relationships, they provide sufficient empirical evidence to conclude that causal relationships do indeed run in both directions: economic conditions affect migration flows and migration flows affect economic conditions. How can both effects be accounted for in a projection model?

The simplest case is a two-equation simultaneous model of migration and employment:

$$\mathrm{MIG} = \alpha_0 + \alpha_1\mathrm{EMP} + \alpha_2\mathrm{WAGE} + \mu_1$$
$$\mathrm{EMP} = \beta_0 + \beta_1\mathrm{MIG} + \beta_2\mathrm{WAGE} + \mu_2$$

where *MIG* is migration, *EMP* is employment, *WAGE* is wages, α and β are the estimated parameters, and μ is the residual. Migration is the dependent variable in the first equation and an independent variable in the second, while employment is the dependent variable in the second equation and an independent variable in the first.

Migration and employment are referred to as endogenous variables because they are determined within this system of equations. *WAGE* is an exogenous variable because it is determined outside the system; it is thought to influence both migration and employment, but not to be influenced by them. This model allows for reciprocal causality: employment affects migration and migration affects employment. The parameters α_1 and β_1 provide estimates of the impact of employment on migration and of migration on employment, respectively.

Parameter estimation in non-recursive models is a complex undertaking. In addition to issues such as identification and the use of instrumental variables, statistical problems occur when an explanatory variable in one equation appears as a dependent variable in another equation. This violates a principal assumption of OLS regression analysis; namely, that explanatory variables are not correlated with residuals. Consequently, OLS regression coefficients are biased and inconsistent. This problem is often handled using special estimation algorithms such as 2- and 3-stage least squares. However, Joun and Conway (1983) found that OLS techniques often produce accurate forecasts and reasonable simulation results, even for non-recursive models. Detailed discussions of these and related issues can be found in Paxton et al. (2011).

9.2 Structural Models: Urban Systems

The second category of structural models is urban systems models. These models are used to determine the distribution of residential and nonresidential activities within urban or metropolitan areas (Anas and Liu 2007; Hunt and Abraham 2005; Pinto and Antunes 2007). Like economic-demographic models, urban systems models incorporate economic factors such as jobs, unemployment rates, and income and use historical data to develop statistical parameter estimates. However, they differ from economic-demographic models in several important ways.

First is geographic scale. Economic-demographic models typically focus on relatively large areas such as nations, regions, states, counties, and metropolitan areas. Urban systems models typically focus on much smaller areas such as census tracts, block groups, traffic analysis zones, and parcels. (Traffic analysis zones are user-designed areas developed for transportation planning; they are typically composed of one or more blocks). Second, the variables used in urban systems models differ from those used in economic-demographic models. Along with jobs, unemployment rates, and income, urban systems models typically incorporate land use (e.g., land costs, development costs, and development potential) and transportation characteristics (e.g., travel costs, times, and distances). Third, urban systems models use a somewhat different set of statistical tools than economic-demographic models. In particular, geographic information systems (GIS) play an important—perhaps essential—role in the implementation of urban systems models (Buliung et al. 2005; Sui 1998). Finally, urban systems models generally require significantly more time and resources to implement than economic-demographic models. One survey found that it typically costs between \$750,000 and \$1,500,000 to implement an urban system model in a large metropolitan area (Johnston and McCoy 2005).

Urban systems models can project not only population but also housing, employment, income, land-use, and transportation characteristics. They can be used to examine a variety of issues that cannot be addressed in most economic-demographic models (e.g., air quality, traffic congestion, loss of open space, and the fiscal implications of land-use decisions). In this section, we discuss models that focus on small geographic areas, incorporate both residential and non-residential land uses, and have links with transportation factors. We do not consider other types of small-area structural models, such as those relying primarily on an econometric approach (Greenwood 1981; Levernier and Cushing 1994).

Urban systems models vary widely in their theoretical approaches, mathematical algorithms, data requirements, and ease of implementation. Presenting a detailed description of these models is beyond the scope of this book, but we can provide an overview highlighting some of the questions they attempt to answer and some of the ways they go about providing those answers.

9.2.1 A Brief History of Urban Systems Models

The 1950s saw the emergence of computer models linking land use, residential and non-residential activities, and the transportation system. Although computers made urban systems models possible, it was sociopolitical conditions that provided the impetus for their development. For example, the desire to use scientific methods to assess the impact of new highways and analyze urban problems spurred the development of new models (Putman 1991, p. 1). Although many early modeling efforts did not succeed, the following 20 years yielded a wealth of information about spatial relationships within urban areas. This period saw the publication of several groundbreaking works revolutionizing urban systems models and urban planning practices (Harris 1965; Lowry 1964).

Lee (1973) wrote a scathing critique of urban systems models and predicted their demise. His main criticisms centered on their overly ambitious but mostly unachieved goals, the lack of sufficient data and computing power, and an inadequate understanding of the urban development process. This influential paper—along with factors such as the lack of technical skills among planners and institutional resistance to new methods—slowed the development and implementation of urban systems models in the United States (Batty 1994; Harris 1994). Although some work continued (Putman 1991), the most important theoretical and practical advances occurred in other countries (Anas 1982; Echenique 1983; Wilson 1974).

More than 40 years have passed since Lee (1973) predicted the demise of urban systems models, but they are more widely used today than ever before. The number of groups working on these models has grown steadily and at least 20 centers on four continents are now actively engaged in urban modeling research (Pinto and Antunes 2007). This resurgence of interest began in the 1990s and was evidenced in a 1994 symposium on urban systems models published by *The Journal of the American Planning Association*. This was the journal's first collection of articles on this topic in more than two decades. One year later the U.S. Department of Transportation and the U.S. Environmental Protection Agency co-sponsored a conference on urban systems models. Many similar conferences have been held since that time.

What accounts for this renewed interest? In part, it stems from two pieces of federal legislation: the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA)—which was reauthorized as TEA21 in 1998 and SAFETEA-LU in 2005—and the Clean Air Act Amendments of 1990. The transportation legislation mandated that transportation plans consider the long-range effects of interactions among land-use patterns, residential and non-residential activities, and the transportation system. The Clean Air Act Amendments specified that the analysis of air quality must take into account interrelationships between travel patterns and the location of homes, businesses, shopping, and recreational activities. In 2008, the State of California adopted Senate Bill 275 that required the use of "advanced" urban models to analyze the effects of urban form and the transportation system on future greenhouse gas emissions. Even without federal mandates, policy-makers are under increasing pressure from environmentalists, developers, and the public to address issues associated with urban form, land use, and the transportation system (Borning et al. 2008; Jin and Fricker 2008). Urban systems models provide a systematic and empirical way to analyze these issues and evaluate policy options.

Equally important are increases in computing power, the development of GIS systems and object-oriented programming, and the greater availability of electronic data (Pinto and Antunes 2007; Stevens et al. 2007). These changes have provided the infrastructure needed to develop and implement urban systems models, overcoming some of the data and technological limitations noted by Lee (1973). Significant advances have also been made in understanding the processes and patterns of urban development (Anas and Liu 2007; de la Barra 2005; Hunt et al. 2005; Wegener 2004). Despite these advances, however, there are still significant challenges regarding theoretical and empirical realism, computational speed, resources, agency skill sets, usability, and the integration of these models into the participatory decision-making process (Timmermans 2003; Waddell 2011).

Urban system models are expensive to develop and implement and are beyond the reach of many agencies. The TELMUT system represents one effort directed at expanding the use of urban system models by reducing the barriers and difficulties in their applications (Pozoukidou 2007; Putman 2010). Rule-based or sketch-planning models also offer simpler alternatives for investigating the interrelationships between land-use and transportation systems. Examples include CommunityViz (Walker and Daniels 2011), WhatIf? (Pettit and Wyatt 2009), and Urban Footprint (Calthorpe Associates 2012).

9.2.2 Components of Urban Systems Models

Urban systems models vary considerably in their theoretical approaches, mathematical designs, data requirements, and ease of implementation, but they typically consist of three major components—regional population and economic forecasts, land use and activity, and transportation. Regional projections are often produced using economic-demographic models such as those discussed in the previous section. The land use and activity component consists of a complex set of procedures for distributing population and economic activities within a region. The transportation component provides projections of transportation system characteristics, such as traffic volumes and speeds on roadways and on public transportation systems.

A fundamental characteristic of urban systems models is the incorporation of explicit, iterative relationships connecting land-use characteristics, activity location, and the transportation system. The transportation system is influenced by land-use configuration and the travel needs of people and businesses and is regulated by government plans and policies. Changes in transportation supply, in turn, affect residential and business location decisions, thus influencing the land-use configuration. *Land use* is a general term covering a variety of characteristics such as housing and employment densities and floor space; residential, commercial, and industrial zoning designations; the supply of buildable land; and local growth policies. Links with the transportation system are often defined as accessibility measures based on travel times, distances, and costs.

Land-use and activity models reconcile the demand for residential and non-residential activities with the available supply of buildable land. One approach is to hold the supply of buildable land constant (Gouldner et al. 1972). If demand exceeds supply, growth shifts to an alternate zone with a sufficient supply of buildable land to support that particular activity. Another approach is to use land-pricing mechanisms to reconcile gaps between supply and demand (de la Barra 2005; Hunt and Abraham 2005; Simmonds 2010). Excess demand can also be satisfied by allowing housing and employment densities to rise (Putman 2010).

Transportation has long been modeled using a four-step approach: trip generation, trip distribution, mode choice, and traffic assignment (McNalley 2007; Southworth 1995). The first step uses trip generation rates to determine the number of trips that occur in each area. These trips are classified by type (e.g., home to work, home to shopping) for zones of origin and destination. The second step matches origins and destinations, creating an origin-destination matrix for all types of trips and all possible pairs of zones. The third step separates trips by mode of travel, such as one-person auto, carpool, public transportation, biking, or walking. Discrete choice logit models are typically used to determine mode choice (Ben-Akiva and Lerman 1985; McFadden 1974; Smirnov 2010). The final step determines the number of trips that occur on particular streets, highways, and transit routes. Traffic assignment accounts for street and highway capacities in order to prevent more trips from occurring than could realistically be expected; it can also simulate the effects of drivers choosing alternative routes because of traffic congestion.

Although four-step models have been in use for almost 50 years, they have been criticized on a variety of grounds (Meyer and Miller 2001). Some analysts claim these models cannot effectively support analyses of contemporary policy concerns such as induced travel, road pricing, vehicle emissions, freight movement, alternative land-use policies, and non-motorized travel (Transportation Research Board 2007). Four-step models are not behavioral in nature and rely on aggregate statistical correlations among demographic and economic variables and travel patterns. Furthermore, they often have difficulty picking up the effects of small changes in the variables and changes in travel behavior that reflect the trade-offs of costs, convenience, and time-savings.

A new generation of highly disaggregated activity-based transportation models has emerged to address these issues (Algers et al. 2005; Bradley et al. 2010; Bhat et al. 2003). In an activity-based model, travel is derived from participation in activities and depends on the organization of those activities. Travel patterns are organized within activity-based models as sets of related trips known as tours. The socioeconomic characteristics of individual households are developed from survey data and other data sources, and are used to project household interactions and travel patterns at a highly disaggregated level. Although activity-based models improve sensitivity to relevant factors in some important new policy areas, there is considerable debate as to how well these advantages can be realized in practice and whether the cost of model development and maintenance can be justified (Virginia Department of Transportation 2009).

9.2.3 Land-Use and Activity Models in Use Today

At least 20 different land-use and activity models have been used in metropolitan areas throughout the world. Although these models share some common features, they represent a wide range of theoretical and empirical perspectives and vary considerably in terms of comprehensiveness, reliability, and implementation (Hunt et al. 2005; Timmermans 2003; Waddell and Ulfarsson 2004; Wegener 2004). In this section, we provide a brief overview of several of the most commonly used models.

9.2.3.1 DRAM and EMPAL: Descendants of Lowry's Gravity Model

Gravity models are based on the idea that interactions between areas *i* and *j* are determined by their relative population sizes and the distance between them. Lowry (1964) developed two gravity models linking the spatial distributions of basic employment (e.g., manufacturing and transportation), population-serving employment (e.g., retail trade and services), and population. A number of models building on this basic framework soon followed (Crecine 1968; Gouldner et al. 1972). Many land-use and activity models in use today are the direct descendants of Lowry's seminal work. Two of the most successful are the Disaggregated Residential Allocation Model (DRAM) and Employment Allocation Model (EMPAL), which have been continuously updated and refined over the last 40 years (Putman 2010).

DRAM and EMPAL are production-constrained spatial interaction gravity models with similar equation structures. Although separate, they are closely integrated with each other. DRAM produces residential projections (households, population, and income) and EMPAL produces non-residential projections (employment). Both models incorporate three important modifications not found in previous models: (1) they use multivariate, multi-parametric attractiveness functions, (2) they include consistent balanced zonal constraint procedures, and (3) they contain additive lagged terms.

DRAM can allocate households into as many as eight income categories and allows up to nine variables in its attractiveness function. A constraint procedure permits the analyst to investigate the effects of policies imposing limits on growth, such as restricting the development of steep hillsides or habitat-preserve areas. The inclusion of a lagged household variable converts DRAM from a purely cross-sectional model into a quasi-dynamic model of household location (Wegener 2004).

EMPAL projects the geographic location of between four and eight categories of employment. Unlike its predecessors, EMPAL does not require the exogenous location of basic employment as a starting point. Rather, basic employment location in this model interacts directly with the location of other activities within the region. This formulation is believed to reflect economic interactions more accurately than previous formulations, especially in light of the declining economic impact of heavy manufacturing industries (Prastacos 1986).

Aggregate spatial interaction models like DRAM and EMPAL have been criticized because they ignore the economics of urban land markets, lack behavioral content, overemphasize the role of transportation, and lack sensitivity to changes in the urban form (Borning et al. 2008; Johnston and McCoy 2005). The economics of land-use and transportation systems are becoming more important as policy-making criteria, especially in this era of tight budgets where the costs and benefits of future projects are hotly debated. The difficulty of these models in assessing the efficacy of compact urban form, walkable communities, and transit-accessible development has highlighted their limitations in the current policy environment. A new generation of urban system models, based on utility-maximizing, discrete choice multinomial logit formulations has been developed to address these limitations. Some of these models are discussed below.

9.2.3.2 PECAS (Production, Exchange, and Consumption Allocation System)

The idea that land and transportation systems might be viewed as markets with endogenously determined prices and costs is rooted in urban economics (Alonso 1964; Wingo 1961). In this tradition, PECAS simulates spatial economic systems by clearing spatial submarkets for various goods and services in a short-run equilibrium, with floor space supply handled separately based on development event probabilities (Hunt and Abraham 2005). PECAS is composed of two modules. One is the activity allocation (AA) module, which runs on a set of land-use areas. AA represents how activities locate within the space provided by developers and how these activities interact with each other at a given point in time and across land-use areas. The other is the space development module (SD), which represents the actions of developers in the provision of space (land and floor space) where activities can locate, including new development, demolition, and redevelopment. SD is a disaggregated model and runs on small grid cells or parcels within each land-use area.

The PECAS AA module represents spatially disaggregated "make" and "use" input-output tables. "Make" tables identify the commodities produced by specific activities and "use" tables define how those commodities are consumed. Commodities include goods and services, labor, and space (land and/or floor space). The movement of these commodities from areas where they are produced to areas where they are consumed is the economic basis for travel and transportation in AA. The transportation system influences the attractiveness of particular areas through its impact on travel distances, costs, times, and associated (dis)utilities.

For each commodity, a three-level nested logit model (derived from a single utility function using random utility theory) is used to allocate: (1) the quantities purchased among various exchange locations, (2) the quantities sold among various exchange locations, (3) the production and consumption of commodities by activities, and (4) categories of industries and households in various areas. The utility of alternatives in these models is influenced by the prices and characteristics of transporting the commodity to and from exchange locations. Prices are established at exchange locations so that the quantity bought equals the quantity sold; in other words, the spatial allocation procedure assumes that there is a short-run equilibrium in the commodity market.

In the PECAS SD module, each grid cell or parcel has a set of attributes, including: (1) a quantity of existing space, (2) zoning rules specifying the types and densities of space permitted, (3) the costs and fees associated with development of each type of space, and (4) the price (rent) for each type of space. Developers act to change the types of space and/or the quantities of space on parcels or grid cells. A Monte Carlo process determines the specific type of event associated with each parcel. Logit models assign selection probabilities to each event that is permitted according to the permitted space types and quantities. The utility functions in these models calculate the expected net revenues to the developer for the available options, incorporating the prices and the costs for transition, maintenance and servicing in each case.

9.2.3.3 UrbanSim

UrbanSim reflects an interdisciplinary research effort directed toward developing operational tools to support the assessment of land-use, transportation, and environmental policies and plans (Waddell 2002, 2011). It has both aggregated and disaggregated components and emphasizes behavioral theory and transparency. This approach leads to an explicit treatment of individual agents such as households and firms, their locations, and the choices and interactions these agents make. The UrbanSim framework includes an explicit representation of real estate demand, supply, and prices within which agents make decisions. Unlike other urban systems models that use an equilibrium solution at each time point and are not path dependent, UrbanSim predicts dynamic changes over time (Borning et al. 2008; Simmonds et al. 2011).

Rather than a single model, UrbanSim is a family of models employing a range of techniques and approaches. Household and economic mobility models focus on the relocation decisions of households and firms. These models allocate new and moving households to residential locations and allocate firms to non-residential locations. Variables used in the household-location model include attributes of housing (e.g., price, density, and age), neighborhood characteristics (e.g., land use, density, average property values, access to retail establishments), and regional accessibility to jobs. The employment-location model includes real estate characteristics (e.g., price, type of space, density, age), neighborhood characteristics (e.g., average land values, land-use mix, employment), and regional accessibility to population. The real estate development model uses a multinomial logit model that simulates development choices (e.g., no change, new development, and redevelopment). Variables in this model include characteristics of the area (e.g., current development, policy constraints, land and improvement values), characteristics of the site location (e.g., proximity to highways, arterials, and existing development), and regional accessibility to population. The land-price model uses hedonic regression techniques to estimate changes in land prices as the characteristics of locations change over time.

9.2.3.4 DELTA

The DELTA land-use/economic modeling package has been developed since the mid-1990s (Simmonds 1999, 2010). It consists of four components: (1) a transportation model, (2) an economic model, (3) an urban activity model, and (4) a migration model. DELTA is designed to allow interactions among these four components. The transportation and urban activity models are applied at the small-area level, whereas the migration and economic models are applied at larger levels of geography.

DELTA uses a spatial input-output model to forecast sectors of the economy. These forecasts are influenced by changes in output and productivity, costs of transportation (from the transportation model), consumer demands for goods and services, and commercial rents (from the urban activity model). Changes in employment by sector are passed to the urban activity model, which forecasts the location of households and jobs within the larger area. Residential and non-residential locations are influenced by the supply of floor space, accessibility, and environmental variables. Household location decisions are influenced by accessibility to workplaces and services, and business location decisions are influenced by accessibility to potential workers and customers. The locations of households and jobs interact with the transportation model to generate travel demands. Households determine consumer demand for goods and services in each area for use in the economic model. The rents arising from competition for property in each area affect both the economic and migration models. The migration model forecasts migration among the larger areas based on job opportunities and housing costs from the urban activity model.

The urban activity component is implemented through four submodels. In the transition submodel, household and demographic changes are expressed as rates of household formation, changes from one status to another (e.g., couples without children to couples with children), and household dissolution. More complex changes are represented by combinations of transition rates, which are (at present) independent of other factors within the model. The car-ownership submodel predicts the changing proportion of households having 0, 1, and 2+ cars, mostly in response to changes in income. The location submodel model predicts the relocation of households and jobs, given the property markets in which they are competing for space. The employment status submodel is the one part of the package that works primarily in terms of persons rather than of households. It first calculates the demand for labor by socioeconomic group, given the number and location of new jobs by sector. The second stage of this submodel adjusts the employment status of economically active individuals and the commuting patterns of workers until the required number of workers is supplied to each zone.

DELTA also has development and area-quality submodels. The development submodel predicts the operation of the private sector development process. This submodel takes into account the effect of the planning system, measured through the quantities of each type of development permitted in each small area. Developers are motivated by the expected profitability of development, estimated by comparing rents with construction costs. The area-quality submodel deals with the existence of positive and negative cycles of urban quality. Positive influences result from rising average incomes, declining vacancy rates, and similar factors. This submodel is important to the overall design of the model because it represents processes that tend to maintain or to enhance the differences between more and less prosperous areas within cities.

9.2.3.5 RELU-TRAN

RELU-TRAN is a spatially disaggregated general equilibrium model of a metropolitan economy and its land use that is based on a number of models that have been developed over the past 30 years (Anas 1982; Anas and Arnott 1997; Anas and Liu 2007). Rather than using linear, quadratic, or other standard programming methods, RELU-TRAN requires the solution of highly non-linear equations systems using non-standard and innovative iterative algorithms that exploit the special features of those equations. Numerical solutions of models using iterative techniques are not well practiced within the field of transportation and land-use modeling, but are gaining broader applicability to solve a variety of problems (Anas and Liu 2007; Judd 1998).

Based on microeconomic theory, RELU-TRAN equilibrates floor space, land and labor markets, and markets for the products of industries. Product markets include development (construction and demolition), spatial inter-industry linkages, commuting, and discretionary travel. People can re-locate to residences or jobs outside the area; income can originate either inside or outside the area; assets inside the area can be owned by outsiders; and firms can purchase inputs produced either inside or outside the area. Each person makes choices concerning whether to work, where to work, and where to reside. These decisions are subject to a budget constraint (e.g., rent values, travel costs, income, and taxes) and are assumed to maximize utility. Landlord behavior depends on the short-run supply of building floor space. A landlord operates floor space by maximizing profit under perfect competition and the only decision a landlord makes is to offer floor space for rent or withhold it from the market. Developers are profit-maximizing, competitive firms; they take building prices and construction and demolition costs as given. Developers buy vacant land (or a building) and decide whether and what kind of building to build (or whether to demolish an existing building).

9.3 Microsimulation Models

Population projections have been made at progressively lower levels of geography in recent decades. Taking this trend to its logical conclusion implies the development of models based on the activities of individual units, such as persons, households, vehicles, organizations, or firms. These are known as microsimulation models (from *microanalytic simulation*). They are able to perform highly detailed analyses of activities such as highway trips, financial and economic transactions, and demographic changes.

Microsimulation models are distinguished from other projection models in that they operate at the level of individual units, with each unit represented by a record containing a unique identifier and a set of associated attributes (e.g., a list of persons with age, sex, income, and pension status or a list of vehicles with origin, destination, and operational characteristics). These models start with a database containing estimates of the characteristics of each individual unit; these estimates are often based on synthetic estimation techniques (Muller and Axhausen 2011; Rahman et al. 2010; Williamson 2013). A set of rules (i.e., transition probabilities) is applied to each unit, leading to simulated changes in its status and behavior over time. These rules may be deterministic (e.g., changes in tax liability resulting from changes in tax regulations) or stochastic (e.g., probabilities of dying, marrying, giving birth, or moving). In either case, the rules lead to a variety of outcomes. Importantly, the outcomes reflect both overall aggregate changes and the ways in which those changes are distributed across populations and geographic areas.

Microsimulation as a tool for policy analysis has a long history (Mitton et al. 2000; Orcutt et al. 1976; Troitzsch et al. 2010). The motivation behind microsimulation models is that aggregate behavior is determined by the decisions made by many individuals; therefore, it is useful to develop models of the activities of individual units. This framework is well suited for analyzing problems that require the modeling of interactions among policies and a variety of economic, social, and demographic conditions. For instance, microsimulation models have been used to assess the distributional implications of changes in social security, personal taxes, and pensions (Panis and Lillard 1999; van Sonsbeek 2011); the implications of changing income thresholds for the payment of state benefits (Brown and Harding 2002); disability costs faced by older persons (Morciano et al. 2012); and the effects of changes in transportation and land-use policies on travel patterns (Bradley et al. 2010; Vovsha et al. 2002).

Microsimulation models have also received attention as a population projection tool (Andreassen 1993; Harding and Gupta 2007; Zinn et al. 2010). Non-spatial projection models include APPSIM in Australia (Harding et al. 2010), SADNAP in the Netherlands (van der Werf et al. 2007), DEMOSIM in Canada (Malenfant et al. 2011), and a model covering the Houston-Galveston metropolitan area (Messen and Joshi 2010). Spatial projection models rely heavily on the methods developed for non-spatial models, but seek to address geographical questions as well (Tanton and Edwards 2013). Ballas et al. (2005) describe SMILE, a spatial microsimulation model designed to analyze the impact of policy changes and economic development in rural areas in Ireland. Wu and Birkin (2013) describe Moses, a spatial microsimulation model that projects the population of the United Kingdom through discrete demographic processes at a fine spatial scale. A number of urban system models have also adopted a spatial microsimulation framework, including UrbanSim (Waddell et al. 2003), ILUTE (Salvini and Miller 2005), ILUMASS (Moeckel et al. 2007), and RAMBLAS (Veldhuisen et al. 2000).

There are significant challenges in implementing microsimulation models. Development costs, maintenance requirements, and agency skill sets present substantial barriers because these models typically require investments of several person-years to develop and additional person-years to maintain (Edwards 2010; Harding 2007). It is difficult to develop reliable base data and reasonable transition probabilities; in fact, the lack of high-quality, comprehensive, longitudinal socioeconomic data often forces modelers to generate less reliable synthetic data for building behavioral transitions. Stochastic variability is another issue (Salvini and Miller 2005). Testing the stability of a microsimulation model is important, as multiple runs (in cases where random effects exist) may result in significantly different results even when the inputs are the same. Ease of use, long run-times, and assessment (validation) of results are also critical issues in implementation (Birkin 2013; Harding et al. 2010).

Microsimulation models reflect complex real-life events and provide a valuable tool for analyzing both the aggregated and disaggregated effects of existing policies and proposed policy changes. Despite the challenges involved in their development and implementation, major advances have been made in the techniques used to create and validate these models. Microsimulation models meet the increasing demand for highly disaggregated projections and it is likely that efforts to refine and improve them will continue. Clarke and Harding (2013), Harding (2007), Gilbert (2008, pp. 1–6), Heppenstall et al. (2012), and Mainzer and Chua (2012) discuss the similarities and differences between microsimulation models and several other individual-level modeling approaches.

9.4 Conclusions

Structural and microsimulation models require more resources and are more difficult to implement than other projection methods discussed in this book. They require a large amount of base data, sophisticated model-building skills, complex statistical procedures, and intricate computer programs. These requirements make them costly to develop, apply, and maintain, putting them out of reach for many organizations.

Are these models worth the effort and resources they require? The answer to this question depends on the purposes for which the projections will be used. If the only objective is to enhance forecast accuracy, these models are not worth their added cost and complexity. The accuracy of population projections from structural and microsimulation models is heavily dependent on the accuracy of the base data, synthetic populations, transition probabilities, projections of the model's independent variables, and assumptions regarding the model's structure and its stability over time. As we show in Chap. 13, there is no evidence that more complex models provide more accurate population forecasts than can be obtained from simpler, less expensive methods.

For a number of purposes, however, structural and microsimulation models are very useful. Perhaps their greatest advantage is their ability to address a wide range of theoretical, policy, and planning questions (Borning et al. 2008; Mitton et al. 2000; Treyz 1995). Decision making and planning at all levels increasingly require detailed information on a broad array of inter-related variables, geographic areas, and individual behaviors. Structural and microsimulation models are well suited to meet these needs. In addition, they can provide population projections that are consistent with a variety of employment, transportation, land-use, and other types of projections. This attribute is extremely important in many circumstances.

Structural and microsimulation models are much more useful than other projection methods for purposes of simulation and scenario analysis. Although other methods (particularly the cohort-component method) can be used for developing simulations and analyzing alternative scenarios, structural and microsimulation models permit the investigation of a wider range of variables and inter-relationships. They can also be used to evaluate the implications of particular decisions and to suggest policy changes when these decisions lead to unintended or undesirable consequences (Bargain 2007; Schmidt et al. 1997; Tayman 1996).

In some circumstances, simulations and scenario analyses are considerably more important than the development of a specific projection or forecast. For example, what impact would greater labor productivity and higher wages have on migration into an area? How might changes in the age structure affect the demand for housing? What effect would a more restrictive U.S. immigration policy have on the local economy? What effect would a 15% cut in the defense budget have on an area's population growth? How would a policy restricting residential development affect land prices and housing affordability? What impact would greater housing density have on traffic patterns and air quality? What impact would a new baseball stadium have on the geographic distribution of residential and non-residential development? How would location- or time-specific pricing influence the use of public transportation? These and many other questions can be investigated most thoroughly within the framework of structural and microsimulation models, which may explain why these models are more widely used today than ever before.

Finally, data users and decision makers often view projections from structural and microsimulation models as being more authoritative than projections from other methods. It is widely understood that wages and employment opportunities affect migration patterns, that land-use and transportation characteristics affect decisions regarding where people live, and that pricing mechanisms affect travel behavior and the location of households and firms. Data users and decision makers may therefore conclude that models incorporating these and similar factors are more credible than models that exclude them. In fact, they may even equate model complexity with forecast accuracy. These perceptions often give structural and microsimulation models an advantage over other projection methods; this advantage may be particularly important when projections must be defended in a public (and perhaps highly politicized) forum. We address these issues more fully in Chaps. 12 and 13.

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Chapter 10
Special Adjustments

Population projection models can be applied in a relatively straightforward manner in many situations, without consideration of any factors beyond those discussed in previous chapters. However, there are circumstances in which the model must be adjusted to account for confounding characteristics or events. One of the most common adjustments is for special populations such as college students and prison inmates. Failing to account for special populations can lead to unreasonable and inconsistent projections. Whether any specific set of projections requires an adjustment, of course, is a question that must be answered on a case-by-case basis.

There are also circumstances in which a set of projections must be controlled to an independent projection or adjusted to provide additional temporal or age detail. In this chapter, we discuss the circumstances in which unadjusted projections might provide unacceptable results and describe ways for making the necessary adjustments. We also describe several methods for controlling to independent projections and interpolating within age groups or between target years. The adjustments described in this chapter increase the complexity of the projection process, but often lead to substantial improvements in the quality and usefulness of the projections.

10.1 Special Populations

A special population is a group of persons located in an area because of an administrative or legislative action (Pittenger 1976, p. 205). Common types include college students, prison inmates, residents of nursing homes, and military personal and their dependents. Special populations complicate the projection process because their growth or decline is not necessarily determined by the same factors affecting the rest of the population; consequently, they often follow different growth trends.

Special populations typically have different demographic characteristics as well. For example, military personnel and college students are concentrated primarily in

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the young adult ages, residents of nursing homes are concentrated primarily in the older ages, and prison populations often have a high concentration of males and racial minorities. Another confounding characteristic is that special populations may not age in place like other population groups. Instead, their age structures may remain stable over time. For example, a college town sees a large inflow of persons aged 17–19 and a large outflow of persons aged 21–23 every year. Consequently, a substantial proportion of the town's young adult population replaces itself repeatedly rather than aging in place.

Special populations do not create problems for population projections if they comprise a small proportion of the total population or if their growth rates and demographic characteristics are similar to the rest of the population. In these circumstances, no special adjustments are needed. When special populations follow different trends and account for a substantial proportion of the total population, however, adjustments must be made.

Unfortunately, there is no rule of thumb defining "different" or "substantial." Consequently, the analyst must evaluate each situation separately, focusing on the special population's demographic composition, growth trends, components of growth, and—perhaps most important—its share of total population. It is a good bet that special populations will have a significant impact on projections in areas with a large prison, military installation, college, or university. Nursing homes, boarding schools, and mental institutions are sometimes important as well. The impact of special populations is generally greater in small areas than large areas; for example, a prison may have little impact on the total population of a large county but may comprise the entire population of a census tract.

10.1.1 Accounting for Special Populations

Projections can be adjusted for the impact of special populations by following several steps (Fig. 10.1). First is to create estimates of the "regular" population (i.e., residents that are not part of the special population) by subtracting estimates of the special population from estimates of the total population. Second is to project the regular population, using the methods described in earlier chapters. Third is to project the special population itself, using one of the approaches described below. The final step is to add the projection of the special population to the projection of the regular population.

How can special populations be projected? One approach is to develop a cohort-component model for the special population itself, using fertility, mortality, and migration rates that pertain specifically to that population (Pittenger 1976, p. 205). This approach will be useful if the special population accounts for a large proportion of the total population, if the necessary data are available, and if reasonable assumptions about future trends in fertility, mortality, and migration rates for the special population can be made. Data limitations often make this approach impractical, especially for small areas.

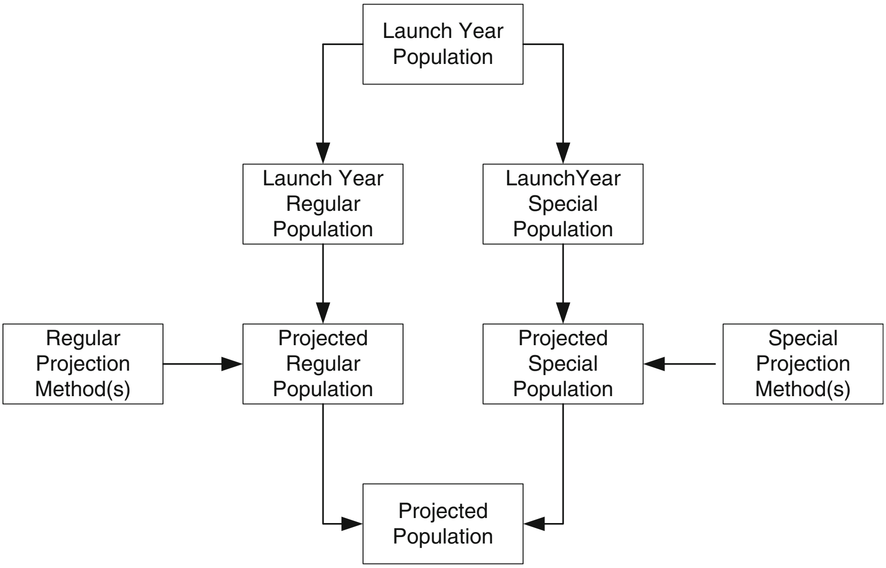

Fig. 10.1 Accounting for special populations

Another approach is to hold the special population constant over the course of the projection horizon. This approach will be useful if the size and demographic composition of the special population has been relatively stable over time and is expected to remain so in the future. It will also be useful if the direction and magnitude of future changes are completely unpredictable at the time the projection is made; if increases and declines are equally likely, it often makes sense to hold the population constant.

Finally, projections of special populations can be based on historical trends or information collected from the administrators of facilities such as colleges, prisons, or nursing homes. Administrators often have information on planned changes in the facility's capacity and enrollment. This information can be used in conjunction with the analyst's judgment regarding future population trends (Smith and Rayer 2012). Combinations of several approaches can also be used, such as holding the demographic composition of the special population constant while allowing for changes in its total size.

10.1.2 Data Sources and Adjustments

Data for special populations are often available from government agencies (e.g., inmates in state prisons) and specific institutions (e.g., students enrolled in a college or university). These data often include breakdowns by age, sex, race, and/or ethnicity. Data regarding the components of growth for special populations, however, generally are difficult to obtain. This can create problems not only for projections of the special population itself, but also for projections of the regular population in places where the special population constitutes a substantial proportion of the total population.

County-level in-migration data for some special populations can be obtained from the American Community Survey (ACS), using either summary files or Public Use Microdata Sample (PUMS) files. Data are available for persons residing in group quarters facilities such as military barracks, prisons, and college dormitories, but not for military dependents (i.e., the spouses and children of military personnel) and for college students *not* living in dormitories. Estimates for these groups can be made using PUMS data that identify all households headed by military personnel or students, but these estimates are far from perfect. Since PUMS data are available only for counties and subcounty areas with 100,000 residents or more, they cannot be used for small area projections.

Migration data for residents of group quarters present a problem even when they are available. ACS data refer to migration over a 1-year period, but group quarters status is noted only for the estimate year. For example, the 2010 ACS provides migration information for persons who resided in group quarters facilities in 2010, but not for persons who resided in those facilities in 2009. This creates a problem for constructing out-migration rates because group quarters status in the earlier year is at least as important as group quarters status in the later year (perhaps more important).

It is also difficult to obtain mortality and fertility data specific to special populations. Birth and death certificates in some counties identify persons associated with the military, but this is the exception rather than the rule. Fertility and mortality data pertaining to other special populations are even more difficult to obtain. If these data are needed, the analyst may simply have to make an educated guess. Fortunately, the development of fertility and mortality rates specific to a special population is generally unnecessary, either because the special population's contribution to births and deaths is very small or because rates for the special population are similar to rates for the population as a whole. The military population (including dependents) may be an exception because fertility rates for this group are often higher than for the non-military population. If the military population comprises a substantial portion of the total population, it may be advisable to account separately for its fertility behavior (see Box 10.1).

Obtaining special population data is considerably more difficult for subcounty areas than for counties. The decennial census provides subcounty-level data on the number and age/sex characteristics for some types of special populations but not for others. There are several ways to deal with the lack of special population data. One is to identify a small area—such as a census tract or individual block—in which the entire population belongs to the special population group. In instances like this, data defining the total population also define the special population. Those data can then be used to estimate the characteristics of similar special populations in nearby areas. For example, suppose that projections are to be made for a census tract containing a prison. Suppose further that two particular blocks within that census tract are

Box 10.1 Estimating Military Birth Rates

Birth certificates in some counties report the military status of parents, providing an excellent source of data on military births. In most counties, however, birth certificates do not include this information. Administrators of military installations sometimes maintain birth data, but gaining access to those data is often difficult. When complete data on military births are available, the analyst can easily develop estimates of military birth rates and incorporate them directly into the projection process. Unfortunately, such data are seldom available. How can estimates of military birth rates be developed for places lacking these types of data?

One possibility is to use PUMS data from the ACS to calculate child-woman ratios (CWRs) for the military and total populations. An adjustment factor can be developed by forming a ratio of the military CWR to the total CWR. Estimates of military age-specific birth rates (ASBRs) can then be made by applying this adjustment factor to the ASBRs calculated for the entire population. This approach assumes—perhaps incorrectly—that the pattern of ASBRs is the same for military and non-military populations.

Another possibility is to obtain information on births occurring in military hospitals. This information can be obtained directly from the hospital or from birth certificates. Although useful, this information excludes data on births to military families that did *not* occur in military hospitals. When direct information on military births is not available, the analyst may have to combine information from a variety of sources to estimate military birth rates. Developing reasonable estimates may require a substantial degree of thought and creativity.

identified as containing solely prison inmates. The demographic characteristics of those two blocks can be used as an estimate of the characteristics of the prison population for the entire census tract.

We have also found the use of proxy rates from similar areas or similar subgroups to be helpful in places where special populations constitute a substantial proportion of the total population. For example, if the opening of a prison had a substantial impact on the age-specific migration rates observed for males in a particular county, it would not be a good idea to use those rates for constructing projections of the regular population. This problem can be dealt with by using age-specific migration rates for females for projections of both males and females (migration rates for males and females are often similar). Alternatively, age-specific rates for males in counties with similar demographic characteristics could be used. Solutions like these may not be perfect, but they are better than making no adjustments at all.

The presence of a special population is a red flag warning the analyst to pay special attention to the data and assumptions used in the projection model. If the special population is large enough and differs significantly from the rest of the population in terms of its demographic characteristics and growth rates, it must be accounted for separately in the projection model. Sometimes the data for making the necessary adjustments are readily available, sometimes they are not. When data are unavailable, the analyst will have to become particularly creative. Developing reasonable adjustments for special populations is essential for developing reasonable population projections.

10.1.3 Illustrating the Impact of a Special Population

We show two examples to illustrate the impact of special populations on population projections. The first uses data from San Diego County, California to illustrate the impact of a large military population on a projection. San Diego has one of the largest concentrations of military personnel in the United States. In 2010, the uniformed military personnel (89,270) accounted for 2.9% of the county's total population. This population is heavily male (91%) and is concentrated in the 18–29 age group (69.7%). Given their numbers and age distribution, the uniformed military population is likely to have a substantial impact on projections by age for San Diego County.

We developed two alternative sets of population projections for males in San Diego County, both using 2010 as a launch year and 2015 as a target year. One set used a basic (i.e., unadjusted) cohort-component model and the other used an adjusted model that separated uniformed military personnel from the civilian population. In the basic model, net migration rates were based on the *total* population. In the adjusted model, net migration rates were based on the *civilian* population and were applied solely to that population. An independent projection was made for the uniformed military population, in which it was assumed that no change in that population would occur after 2010. The fertility and mortality assumptions used in the two models were identical.

Net migration age patterns for the two models are shown in Fig. 10.2. The basic model shows high levels of net in-migration for ages 15–19 and 20–24, followed by net out-migration for age 25–29. These patterns were strongly affected by movements in the military population. The adjusted model shows net in-migration for all three groups, but at much lower levels for ages 15–19 and 20–24. This is a more typical pattern for an area with net in-migration.

Table 10.1 shows projections of the male population from the basic and adjusted models. The two projections of total population are very similar, differing by only 259. However, there are significant differences in some age groups. For ages 15–19 and 20–24, projections from the basic model *exceed* those from the adjusted model by 5.6% and 7.3%, respectively; for ages 25–29, projections from the basic model

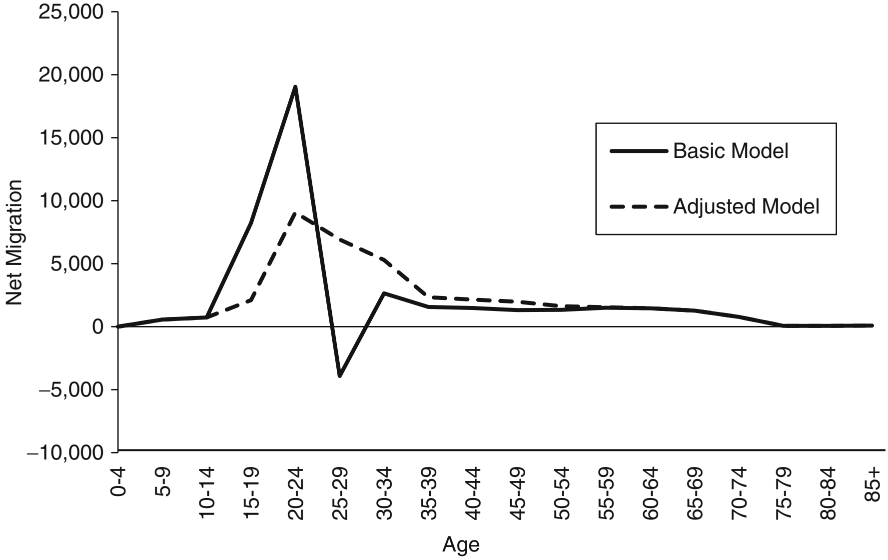

Fig. 10.2 Male net migration by age group, San Diego County, 2010–2015

Table 10.1 Alternative projections of the male population, San Diego County, 2015

	Cohort component model		Difference[a]	
Age	Basic[b]	Adjusted[c]	Number	Percent
0–4	115,269	115,269	0	0.0
5–9	104,312	104,312	0	0.0
10–14	99,989	99,989	0	0.0
15–19	109,955	103,830	6,125	5.6
20–24	136,981	127,029	9,952	7.3
25–29	144,232	155,178	−10,946	−7.6
30–34	133,264	135,965	−2,701	−2.0
35–39	113,633	114,454	−821	−0.7
40–44	106,982	107,720	−738	−0.7
45–49	105,265	105,986	−721	−0.7
50–54	109,484	109,819	−335	−0.3
55–59	103,257	103,314	−57	−0.1
60–64	85,913	85,926	−13	0.0
65–69	69,177	69,189	−12	0.0
70–74	44,997	44,989	8	0.0
75–79	29,528	29,528	0	0.0
80–84	21,530	21,530	0	0.0
85+	23,224	23,224	0	0.0
Total	1,656,992	1,657,251	−259	<−0.1%

[a]Basic model − adjusted model
[b]No adjustment for uniformed military population
[c]Separate projections for uniformed military and civilian populations

Table 10.2 Alternative projections of the total population, census tract 100.14, San Diego County, 2020

			2020[a]	
Population	1990	2010	Basic[b]	Adjusted[c]
Prison	0	6,300	n/a	6,300
Regular	200	11,379	n/a	16,969
Total	200	17,679	26,419	23,269
% in Prison	0%	36%	n/a	27%

[a]Based on the simple linear extrapolation technique
[b]No adjustment for the prison population
[c]Separate projections for prison and non-prison populations

are 7.6% *below* those from the adjusted model. In general, the basic model tends to overstate the population aged 15–24 and understate the population aged 25–54. Differences between the two models were very small for ages 55 and above. We believe that by separating the military and civilian populations, the adjusted model provides more realistic projections of the young adult age groups.

Our second example uses census tract 100.14 in southern San Diego County, which contains a state prison and a county detention facility. In 2010, these two facilities contained 6,300 prisoners, which accounted for 36% of the census tract's population (see Table 10.2). We developed two alternative projections of total population for this census tract, using 1990–2010 as the base period and 2020 as the target year. Both projections were based on the linear extrapolation (LINE) method. One used the trend in the total population and the other used the trend in the regular (i.e., non-prison) population. In the latter, the prison population was projected to remain constant at its 2010 level.

Accounting separately for the prison population leads to a 2020 projection that is 3,150 persons lower (−11.9%) than the projection based on the trend in the total population. The average annual changes in the prison and regular populations over the base period were 315 and 559, respectively. The failure to adjust for the impact of the prison population implies that the prison population will continue to grow by 315 per year. This is highly unlikely because the prison is already occupied above its capacity level.

These examples illustrate the impact special populations can have on population projections. The effects would be even greater if the projections were extended further into the future. In circumstances like these, it is important to take explicit account of special populations when making population projections.

10.2 Controlling

Analysts making population projections often face two distinct but related problems. One is how to make projections of demographic composition (e.g., age, sex, race) match an independent projection of total population or migration. The second is how to make projections for a number of geographic areas add up to an independent projection for a larger area (e.g., how to make the sum of census tract projections match a county projection). *Controlling* is the term we use to describe this adjustment process; *raking* is another commonly used term.

There are several reasons for controlling one set of projections to another. One is the requirement that a set of projections be consistent with an "official" projection that has been developed, adopted, or sanctioned by a governmental body or some other decision-making unit. Another is to tie projections of demographic composition or geographic distribution from an older set of projections to a projection of migration or total population from a more recent set. Perhaps most important, controlling facilitates the construction of projections that are consistent across demographic subgroups and geographic areas; it ensures that projections of demographic characteristics sum to projections of total population and that projections for small geographic areas sum to projections for larger geographic areas.

10.2.1 Controlling to Independent Projections

In this section, we describe several methods for controlling projections of demographic characteristics to independent population or migration projections. We illustrate these methods using a 2015 projection of females in Pima County, Arizona based on a cohort-component model and 5-year net migration data. These projections have a launch year of 2010 and use 2010 birth and survival rates and 2000–2005 net migration rates (derived from the forward survival rate method described in Chap. 6). In the first two illustrations, we control the age distribution from the initial projection for 2015 to an independent projection of the total female population for the same year. In the third illustration, we control the initial net migration projections by age to an independent projection of total female net migration.

10.2.1.1 Projections of Total Population

The simplest method for controlling demographic characteristics to an independent projection of total population is to use a raking procedure based on a single adjustment factor. This factor can be computed by dividing the total population from the independent projection by the total population from the initial projection. The initial projections for each demographic subgroup are then adjusted by multiplying each one by the adjustment factor:

$$\mathrm{FACTOR_t} = \mathrm{CNTLP_t}/\mathrm{P_t}$$
$$\mathrm{CP_{c,t}} = (\mathrm{P_{c,t}})\,(\mathrm{FACTOR_t})$$

Table 10.3 The raking method: Controlling to an independent projection of the female population, Pima County, 2015

Age	2015 Projection Initial[a]	Controlled[b]	Difference[c]	Change 2010–2015[d]
0–4	30,440	30,919	479	457
5–9	30,533	31,013	480	631
10–14	30,500	30,979	479	750
15–19	32,445	32,955	510	−2,190
20–24	40,849	41,491	642	4,650
25–29	34,970	35,520	550	2,931
30–34	31,470	31,965	495	2,066
35–39	30,121	30,595	474	1,451
40–44	30,005	30,477	472	1,805
45–49	29,570	30,035	465	−2,666
50–54	34,327	34,867	540	59
55–59	37,194	37,779	585	4,227
60–64	36,352	36,923	571	6,234
65–69	32,663	33,176	513	8,450
70–74	24,928	25,320	392	6,428
75–79	17,920	18,202	282	3,148
80–84	13,024	13,229	205	818
85+	14,331	14,556	225	1,926
Total	531,642	540,001	8,359	41,175
Initial population projection			531,642	
Independent population projection			540,000	
Adjustment factor[e]			1.015721	

[a]Projection developed by authors
[b]Initial projection × adjustment factor
[c]Controlled projection − initial projection
[d]Controlled projection − 2010 population
[e]Independent population projection / initial population projection

where $FACTOR_t$ is the adjustment factor in target year t; P_t is the initial projection of total population in the target year; $CNTLP_t$ is the independent projection of total population in the target year (i.e., the control total); $P_{c,t}$ is the initial projection for demographic subgroup c in the target year; and $CP_{c,t}$ is the controlled projection for subgroup c in the target year.

Table 10.3 shows the initial and controlled projections for the female population of Pima County in 2015. The initial (uncontrolled) projection is 531,642 and the independent control total is 540,000, yielding an adjustment factor of 540,000/531,642 = 1.015721. The adjusted (controlled) projection for each age group is computed by multiplying the original projection by 1.015721. The sum of the adjusted age groups is equal to the independent total of 540,000 (within rounding error).

In this example, projections of age groups for females were controlled to an independent projection of the total female population. The same method can be applied using different demographic subgroups and different control populations. For example, projections of males and females could be based either on a different adjustment factor for each sex or on a single adjustment factor for both sexes. If the projections are further specified by two ethnic categories (e.g., Hispanic and non-Hispanic), projections for Hispanic males, Hispanic females, non-Hispanic males, and non-Hispanic females could be based on four separate adjustment factors (one calculated separately for each sex/ethnic group), on two separate adjustment factors (one for each ethnic group), or on a single adjustment factor based on the controlled and uncontrolled projections of the total population.

The choice of the appropriate control group will depend on the availability and reliability of independent projections for various demographic subgroups. For subgroups with similar growth characteristics, it is generally not necessary to develop separate control totals and adjustment factors. The main thing to remember when applying this method is that the sum of the demographic subgroups for which adjustments are made must equal the control total used in computing the adjustment factor (within rounding error).

10.2.1.2 Projections of Population Change

The first approach to controlling works well when the adjustments are moderate or small. When adjustments are large, this approach may produce unsatisfactory results because some demographic subgroups may be adjusted by a larger or smaller amount than is warranted. In these circumstances, a method that focuses on population change over the projection interval rather than the population in the target year may produce better results.

The steps for applying the second approach are simple. First, changes in total population over the projection interval are calculated for both the independent projection and the initial projection. Second, a ratio of the two projected changes is formed and applied to the change initially projected for each demographic subgroup, producing a set of adjusted changes. Finally, these adjusted changes are added to the launch year population totals for each subgroup to provide a controlled projection for the target year.

Although the concept underlying this approach is simple, its implementation becomes more complicated when some demographic subgroups are projected to increase while others are projected to decline. To illustrate this problem, suppose that there are only two subgroups. One is projected to increase by 250 and the other to decline by 150, implying a total population change of 100. Suppose further that the projected change for the independent projection (i.e., the control total) is 120. These numbers produce an adjustment factor of $120/100 = 1.2$. Applying this factor to the changes originally projected for the two subgroups (250 and -150) produces adjusted changes of 300 and -180. These changes add to 120, which is consistent with the change for the independent projection. However, the adjustment causes the subgroup losing population to lose even more than was initially projected. Given that projected growth for the entire population has been adjusted upward, this may not be a reasonable outcome.

This points to an important problem with using a simple raking procedure for adjusting projected population changes: when some demographic subgroups are projected to increase and others to decline, a raking procedure based on a single adjustment factor causes both population gains and losses to become larger or smaller (depending on the direction of the adjustment). This is not a logical outcome. In most instances, a better outcome would be that adjustments for all demographic subgroups are positive when the overall adjustment is upward and negative when the overall adjustment is downward.

This can be accomplished by using two separate adjustment factors—one for subgroups projected to grow and one for subgroups projected to decline. This adjustment procedure is known as the *plus-minus* method (Judson and Popoff 2004). The equations for the plus-minus method are:

$$\begin{aligned}
&\mathrm{CNTLCHG} = \mathrm{CNTLP} - \mathrm{P_l}\\
&\mathrm{PCHG_c} = \mathrm{P_{c,t}} - \mathrm{P_{c,1}}\\
&\mathrm{ABSUM} = \sum \left|\mathrm{PCHG_c}\right|\\
&\mathrm{SUM} = \sum \mathrm{PCHG_c}\\
&\mathrm{POSFACTOR} = (\mathrm{ABSUM} + (\mathrm{CNTLCHG} - \mathrm{SUM}))/\mathrm{ABSUM}\\
&\mathrm{NEGFACTOR} = (\mathrm{ABSUM} - (\mathrm{CNTLCHG} - \mathrm{SUM}))/\mathrm{ABSUM}\\
&\text{If } \mathrm{PCHG_c} > 0, \text{then } \mathrm{CP_{c,t}} = \mathrm{P_l} + (\mathrm{PCHG_c})\ (\mathrm{POSFACTOR})\\
&\text{If } \mathrm{PCHG_c} < 0, \text{then } \mathrm{CP_{c,t}} = \mathrm{P_l} + (\mathrm{PCHG_c})\ (\mathrm{NEGFACTOR})
\end{aligned}$$

where *CNTLP* is the independent projection of total population (i.e., the control projection); P_l is the total population in the launch year l; *CNTLCHG* is the population change between launch year and target years for the independent projection; $PCHG_c$ is the population change for a demographic subgroup c from the initial (uncontrolled) projection; *ABSUM* is the sum of the absolute values of uncontrolled population changes for each demographic subgroup; *SUM* is the sum of the uncontrolled population changes for each demographic subgroup; *POSFACTOR* is the adjustment factor for demographic subgroups projected to increase; *NEGFACTOR* is the adjustment factor for demographic subgroups projected to decrease; *CP* is the controlled population projection for a demographic subgroup; and Σ represents the sum over all demographic subgroups.

As these equations show, the formulas for the positive and negative adjustment factors are similar, differing only by a single sign in the numerator. In fact, if projected changes for all demographic subgroups have the same sign, the plus-minus method produces the same results as the single-factor raking procedure. It should also be noted that the sum of the two adjustment factors is equal to 2.

Table 10.4 shows the application of the plus-minus method to the projection of females in Pima County. The adjustment factors indicate that population changes for age groups gaining population are increased by just over 18% (1.183757), while population changes for age groups losing population are lowered by the same percentage (0.816243). Comparing the controlled and uncontrolled columns, we see that the adjustment process works as expected. The gains become larger for age groups projected to increase and the losses become smaller for age groups projected to decline.

Table 10.4 The plus-minus method: Controlling to an independent projection of the female population change, Pima County, 2010–2015

Age	2010 population	2015 projection Initial[a]	Controlled[b]	Diff.[c]	2010–2015 change Initial[d]	Abs. value	Controlled[e]
0–4	30,462	30,440	30,444	4	−22	22	−18
5–9	30,382	30,533	30,561	28	151	151	179
10–14	30,229	30,500	30,550	50	271	271	321
15–19	35,145	32,445	32,941	496	−2,700	2,700	−2,204
20–24	36,841	40,849	41,585	736	4,008	4,008	4,744
25–29	32,589	34,970	35,408	438	2,381	2,381	2,819
30–34	29,899	31,470	31,759	289	1,571	1,571	1,860
35–39	29,144	30,121	30,301	180	977	977	1,157
40–44	28,672	30,005	30,250	245	1,333	1,333	1,578
45–49	32,701	29,570	30,145	575	−3,131	3,131	−2,556
50–54	34,808	34,327	34,415	88	−481	481	−393
55–59	33,552	37,194	37,863	669	3,642	3,642	4,311
60–64	30,689	36,352	37,393	1,041	5,663	5,663	6,704
65–69	24,726	32,663	34,121	1,458	7,937	7,937	9,395
70–74	18,892	24,928	26,037	1,109	6,036	6,036	7,145
75–79	15,054	17,920	18,447	527	2,866	2,866	3,393
80–84	12,411	13,024	13,137	113	613	613	726
85+	12,630	14,331	14,644	313	1,701	1,701	2,014
Total	498,826	531,642	540,001	8,359	32,816	45,484	41,175

Calculation of plus-minus adjustment factors:	
Sum of initial pop change (SUM)	32,816
Sum of abs. value of initial pop change (ABSUM)	45,484
2010 population	498,826
Independent population projection	540,000
Independent population change[f] (CNTLCHG)	41,174
Positive adjustment factor[g]	1.183757
Negative adjustment factor[h]	0.816243
Sum of adjustment factors	2

[a]Projection developed by the authors
[b]2010 population + controlled population change
[c]Controlled population projection − initial population projection
[d]Initial population projection − 2010 population
[e]Positive initial population change × positive adjustment factor or negative initial population change × negative adjustment factor
[f]Independent population projection − 2010 population
[g](ABSUM + (CNTLCHG − SUM)) / ABSUM
[h](ABSUM − (CNTLCHG − SUM)) / ABSUM

A comparison of Tables 10.3 and 10.4 shows how the two alternative controlling methods affect the results. In terms of the projections themselves, the differences are not particularly large. In terms of projected changes between 2010 and 2015, however, there are some notable differences. The 0–4 age group provides a good illustration. In the initial projection, this group declined by 22 between 2010 and

2015. When single-factor raking was applied, it increased by 457 (Table 10.3). When the plus-minus method was applied, it declined by 18 (Table 10.4). The plus-minus method thus produced an increase that was much more in line with the initial projection than did single-factor raking. We believe the plus-minus method will generally produce more reasonable results than single-factor raking when some subgroups are increasing and others are declining.

One weakness of the plus-minus method should be mentioned. This occurs when the difference between the control total (CNTLCHG) and the sum of the uncontrolled projections (SUM) exceeds the sum of the absolute values of the uncontrolled projections (ABSUM). When this happens, one of the adjustment factors must be negative, reversing the signs of the projected changes. One solution to this problem is to transform the distribution of projected changes by adding or subtracting a fixed constant to each value before computing the adjustment factors (San Diego Association of Governments 1998). The control total also must be modified by the total amount added to or subtracted from the distribution. After the factors are applied, the controlled values are transformed back to the original scale by the amount of the fixed constant.

10.2.1.3 Projections of Migration

The examples illustrated in Tables 10.3 and 10.4 show how to control population characteristics from one projection to the total population from another projection. In some instances, however, the application may call for controlling to an independent projection of migration rather than to an independent projection of total population. This may occur when migration (rather than total population) is the variable of interest or when the focus is on the components of change rather than population per se. It should also be noted that controlling to an independent projection of total population or population change makes projections of the components of growth inconsistent with projections of total change.

Consider Table 10.3, for example. The controlled projection for the population aged 0–4 in 2015 is 479 persons higher than the projection based exclusively on births and infant deaths (i.e., the initial uncontrolled projection). How many of these additions were the result of a larger number of births? How many were migrants? How many died during the projection interval? There are no satisfactory answers to these questions.

When the focus is on components of change, the most satisfactory solution to this problem is to control to a projection of migration rather than to a projection of population or population change. A new migration projection can be obtained by rearranging the terms in the demographic balancing equation described in Chap. 2. This defines net migration as total population change minus births plus deaths. For females in Pima County, for example, the level of net migration consistent with the population change implied by the independent (control) projection is:

$$(540{,}000 - 498{,}826) - 30{,}527 + 20{,}721 = 31{,}368$$

Table 10.5 The plus-minus method: Controlling to an independent projection of female net migration, Pima County, 2010–2015

Age	2010 population	2015 surv. population[a]	Net migration 2010–2015 Initial[a]	Net migration 2010–2015 Abs. value	Net migration 2010–2015 Controlled[b]	2015 population projection Initial[c]	2015 population projection Controlled[d]	2015 population projection Diff.[e]
0–4	30,462	30,440	0	0	0	30,440	30,440	0
5–9	30,382	30,359	174	174	223	30,533	30,582	49
10–14	30,229	30,366	134	134	172	30,500	30,538	38
15–19	35,145	30,202	2,243	2,243	2,877	32,445	33,079	634
20–24	36,841	35,085	5,764	5,764	7,392	40,849	42,477	1,628
25–29	32,589	36,753	−1,783	1,783	−1,279	34,970	35,474	504
30–34	29,899	32,477	−1,007	1,007	−723	31,470	31,754	284
35–39	29,144	29,765	356	356	457	30,121	30,222	101
40–44	28,672	28,967	1,038	1,038	1,331	30,005	30,298	293
45–49	32,701	28,380	1,190	1,190	1,526	29,570	29,906	336
50–54	34,808	32,205	2,122	2,122	2,721	34,327	34,926	599
55–59	33,552	34,079	3,115	3,115	3,995	37,194	38,074	880
60–64	30,689	32,591	3,761	3,761	4,823	36,352	37,414	1,062
65–69	24,726	29,435	3,228	3,228	4,140	32,663	33,575	912
70–74	18,892	23,180	1,748	1,748	2,242	24,928	25,422	494
75–79	15,054	16,974	946	946	1,213	17,920	18,187	267
80–84	12,411	12,542	482	482	618	13,024	13,160	136
85+	12,630	14,832	−501	501	−359	14,331	14,473	142
Total	498,826	508,632	23,010	29,592	31,369	531,642	540,001	8,359

Calculation of plus-minus adjustment factors:	
Sum of initial net migration (SUM)	23,010
Sum of abs. value of initial net migration (ABSUM)	29,592
2010 population	498,826
Independent population projection	540,000
Independent population change[f]	41,174
Births[a]	30,527
Deaths[a]	20,721
Independent net migration 2010–2015 (CNTLCHG)[g]	31,368
Positive adjustment factor[h]	1.28244
Negative adjustment factor[i]	0.71756
Sum of adjustment factors	2

[a]Projection developed by the authors
[b]Positive original population change × positive adjustment factor or negative original population change × negative adjustment factor
[c]Survived population + initial net migration
[d]Survived population + controlled net migration
[e]Controlled population projection − initial population projection
[f]Independent population projection 2015 − population 2010
[g]Independent projection of population change − births + deaths
[h](ABSUM + (CNTLCHG − SUM)) / ABSUM
[i](ABSUM − (CNTLCHG − SUM)) / ABSUM

In the example shown in Table 10.5, we use the plus-minus method to control the net migration projections to a new net migration total. Since the externally derived migration control total is larger than the uncontrolled projection of net migration, the adjustment process raises migration gains in age groups with net in-migration and reduces migration losses in age groups with net out-migration.

The plus-minus method can also be used to control projections of gross in- and out-migration to an independent net migration control total. In this application, in-migrants are treated as the group with positive changes and out-migrants are treated as the group with negative changes. For example, if the independent projection of net migration were higher than the initial projection, this adjustment would raise the number of in-migrants and reduce the number of out-migrants.

10.2.2 Controlling to Projections of Larger Geographic Areas

Population projections are often prepared for a number of geographic areas and for the composite of those areas (e.g., all counties within a state, all census tracts within a county). In this section, we discuss methods for reconciling projections at different levels of geography. These methods make the sum of the projections for the smaller areas equal to the projection for the larger area.

The simplest way to achieve this reconciliation is to use a bottom-up approach in which the projection for the larger area is simply calculated as the sum of the projections for the smaller areas. A bottom-up approach is most useful when the sum of the projections for the smaller areas is not significantly different from the projection for the larger area.

If the differences are large—or if there are other reasons for holding the projections for the larger area constant—a bottom-up approach will not work. In these circumstances, some type of controlling procedure must be used. If controlling involves only one variable—a single dimension—we can use one of the controlling methods described in the previous section. If controlling involves several variables, however, more complicated procedures must be used. The following examples illustrate single-dimensional and multi-dimensional controlling.

10.2.2.1 Single-Dimensional Controlling

There are 42 subregional areas (SRAs) in San Diego County, each composed of one or more census tracts. The San Diego Association of Governments (2011) constructed a set of population projections by racial/ethnic group for census tracts and SRAs in the county. However, those projections did not include any information from the 2010 census. We created a new set of projections for 2020 for one SRA and its six constituent census tracts in which the initial 2010 projections were adjusted to be consistent with 2010 census counts (not shown here). The projections for the SRA were broken down into several racial/ethnic groups but the projections for census tracts were of total population only. Because of the adjustments, the new SRA projections were no longer consistent with the racial/ethnic breakdown found in the initial census tract projections.

We apply a single-factor raking procedure to illustrate how the initial racial/ethnic projections for census tracts can be controlled to the new SRA racial/ethnic projections. The procedure is very simple. First, the initial census tract projections are added together for each racial/ethnic group. Second, adjustment factors are computed by dividing the new SRA projections by the sum of the initial census tract projections, for each racial/ethnic group. These adjustment factors are shown in the top panel of Table 10.6. Finally, the adjustment factors are multiplied by the initial projections of each census tract for each racial/ethnic group, providing a set of controlled projections (shown in the bottom panel of Table 10.6). The adjustments raise the projections for Hispanics by about 2% but reduce the projections for the other racial/ethnic groups, with particularly large reductions for non-Hispanic whites (−8.5%) and non-Hispanic blacks (−13%).

The controlled racial/ethnicity projections for census tracts now sum to the SRA projection for each race/ethnicity group (except for one small difference due to rounding). However, the projections of total population for each tract are now different than they were initially, as seen by comparing the "Total Pop" columns in the initial and controlled projections. This is the major problem with a single-dimensional controlling procedure: Making projections consistent across one dimension makes them inconsistent across another.

10.2.2.2 N-dimensional Controlling

How can we make the initial census tract projections consistent with the new 2020 SRA race/ethnicity projections *and* the new 2020 census tract projections of total population? The methods discussed so far cannot solve this problem. Rather, a procedure is needed that can control across several dimensions simultaneously; this is sometimes called *n-dimensional controlling*. It can be accomplished using the iterative proportions (IP) method, which approximates a least squares solution in order to obtain convergence in all n dimensions (Deming 1943, Chap. 7; Judson and Popoff 2004). This method can handle a wide range of situations.

Three main conditions must be met in the most common application of the IP method. First, all projections must be greater than or equal to zero. Second, there must be independent projections for the totals of each controlling dimension. For example, if we are controlling census tract projections to a SRA projection by race/ethnicity, we must have independent projections of the total population of each census tract *and* of the SRA's population by race/ethnicity. Third, the sum of all projections over all dimensions must be equal; for example, the sum of the race/ethnicity projections for the SRA must be equal to the sum of the total population projections for the census tracts.

Table 10.6 The raking method: Controlling to a population by ethnic group in a larger area, selected census tracts, San Diego County, 2020

	Initial projection by ethnic group[a]				
Census tract	Hispanic	NH-White	NH-Black	NH-Other	Total pop
208.01	1,010	3,975	40	236	5,261
208.05	1,052	2,158	87	125	3,422
208.06	2,538	3,507	145	350	6,540
208.07	575	1,777	5	132	2,489
208.08	1,670	10,178	193	600	12,641
208.09	2,998	5,027	44	270	8,339
Sum of census tracts[b]	9,843	26,622	514	1,713	
SRA control[c]	10,040	24,380	447	1,676	
Adjustment factor[d]	1.020014	0.915784	0.869650	0.978400	
	Controlled projection by ethnic group				
Census tract	Hispanic	NH-White	NH-Black	NH-Other	Total pop
208.01	1,030	3,640	35	231	4,936
208.05	1,073	1,976	76	122	3,247
208.06	2,589	3,212	126	342	6,269
208.07	587	1,627	4	129	2,347
208.08	1,703	9,321	168	587	11,779
208.09	3,058	4,604	38	264	7,964
Sum of census tracts[b]	10,040	24,380	447	1,675	
SRA control[c]	10,040	24,380	447	1,676	
Difference[e]	0	0	0	1	

[a]2050 Regional Growth Forecast, San Diego Association of Governments, October 2011
[b]Sum of the population projection in each census tract
[c]Independent SRA population projection developed by the authors
[d]SRA control / sum of the population projection in each census tract
[e]SRA control − sum of the controlled population projection in each census tract

We illustrate n-dimensional controlling using the two dimensions described in the previous example. One represents a demographic characteristic (race/ethnicity) and the other represents the total population of several geographic regions (six census tracts and a SRA). The IP method begins with an initial matrix, whose body contains the initial population projections by racial/ethnic group for each census tract in the SRA. The column control total is the new population projection by racial/ethnic group for the larger geographic area (the SRA) and the row control total is the new total population projection for each census tract. These row and column totals are often called *marginals*. The goal of the IP method is to adjust the matrix so that, when summed vertically, census tract projections within each racial/ethnic group equal the SRA projections for the corresponding group and, when summed horizontally, census tract projections across racial/ethnic groups equal the total population for each census tract.

We achieve this goal by applying a single-factor raking procedure over and over, alternating sequentially between rows and columns. Starting with rows, we apply a row-specific raking factor to each cell in each row; we repeat this process for all rows. After this step, the sum of racial/ethnic groups matches the total population for each census tract. However, the sum of projections for all the census tracts within each racial/ethnic group no longer matches the SRA total. We then apply a column-specific raking factor to each cell in each column. After this step, the sum of the cells in each column matches the SRA total for each racial/ethnic group, but the sum of the cells in each row no longer matches the total population for census tracts. By continuing this sequence of adjustments we eventually arrive at a convergence in which cells in both rows and columns sum to the marginal totals (except for small differences due to rounding).

The rate of convergence is relatively fast, typically requiring between two and four cycles of horizontal and vertical adjustments to achieve complete agreement in one dimension and close agreement in the other (Deming 1943, Chap. 7). It does not matter whether one begins the process by adjusting rows or columns; the results are essentially the same. One can refine the IP method to handle both positive and negative adjustments by using the plus-minus method described earlier to determine two separate adjustment factors to use in the iterative process.

Table 10.7 shows the mechanics of the IP method. The first panel ("Beginning Matrix, First Iteration") shows the initial conditions and the elements needed to apply the IP method. The main body of the matrix is contained in columns 2–5 and the rows for the six census tracts; the cells of this matrix show the uncontrolled projections produced by the San Diego Association of Governments (2011). Column 6 shows the sum of the racial/ethnic group projections for census tracts and Column 7 (Census Tract Control) shows the row marginals (i.e., the independent total population projection for each census tract). The row labeled "Sum of Census Tracts" shows the uncontrolled projections by racial/ethnic group for the SRA. The row labeled "SRA Control" shows the column marginals (i.e., the independent racial/ethnic group projection for the SRA).

For columns, the population control totals are smaller than the sum of the uncontrolled projections for all racial/ethnic groups except Hispanics. For rows, the population control totals are smaller than the sum of the uncontrolled projections for all census tracts. The two numbers in bold print (−**2,149**) are particularly important. They represent the total amount of the adjustment required in the rows and columns in order to make the projections consistent across both dimensions; they must be equal for the IP method presented here to work properly. The row and column adjustment factors are computed as the ratio of the control total to the sum of the corresponding cells; they are computed separately for each census tract and each racial/ethnic group. Except for Hispanics, all the adjustment factors in the first panel are below 1.0, indicating that downward adjustments are necessary.

The second panel of Table 10.7 ("Rows Adjusted, First Iteration") shows the population projections by racial/ethnic group for each census tract after we adjusted them to match the row control totals. For example, the adjusted Hispanic population in census tract 208.01 is:

$$(1,010)\ (0.946398) = 956$$

Table 10.7 The iterative proportions method: Controlling a population projection in two dimensions, selected census tracts, San Diego County, 2020

	Beginning matrix, first iteration							
Census tract	Hispanic	NH-White	NH-Black	NH-Other	Sum of ethnic groups[a]	Census tract control	Difference[b]	Row Factor[c]
208.01	1,010	3,975	40	236	5,261	4,979	−282	0.946398
208.05	1,052	2,158	87	125	3,422	3,333	−89	0.973992
208.06	2,538	3,507	145	350	6,540	6,114	−426	0.934862
208.07	575	1,777	5	132	2,489	2,308	−181	0.927280
208.08	1,670	10,178	193	600	12,641	12,224	−417	0.967012
208.09	2,998	5,027	44	270	8,339	7,585	−754	0.909581
Sum of census tracts[d]	9,843	26,622	514	1,713			**−2,149**	
SRA control	10,040	24,380	447	1,676				
Difference[e]	197	−2,242	−67	−37	**−2,149**			
Column factor[f]	1.020014	0.915784	0.869650	0.978400				
	Rows adjusted, first iteration							
Census tract	Hispanic	NH-White	NH-Black	NH-Other	Sum of ethnic groups[a]	Census tract control	Difference[b]	Row factor[c]
208.01	956	3,762	38	223	4,979	4,979	0	1.000000
208.05	1,025	2,102	85	122	3,334	3,333	−1	0.999700
208.06	2,373	3,279	136	327	6,115	6,114	−1	0.999836
208.07	533	1,648	5	122	2,308	2,308	0	1.000000
208.08	1,615	9,842	187	580	12,224	12,224	0	1.000000
208.09	2,727	4,572	40	246	7,585	7,585	0	1.000000
Sum of census tracts[d]	9,229	25,205	491	1,620			**−2**	
SRA control	10,040	24,380	447	1,676				
Difference[e]	811	−825	−44	56	**−2**			
Column factor[f]	1.087875	0.967268	0.910387	1.034568				
	Columns adjusted, first iteration							
Census tract	Hispanic	NH-White	NH-Black	NH-Other	Sum of ethnic groups[a]	Census tract control	Difference[b]	Row factor[c]
208.01	1,040	3,639	35	231	4,945	4,979	34	1.006876
208.05	1,115	2,033	77	126	3,351	3,333	−18	0.994628
208.06	2,582	3,172	124	338	6,216	6,114	−102	0.983591
208.07	580	1,594	5	126	2,305	2,308	3	1.001302
208.08	1,757	9,520	170	600	12,047	12,224	177	1.014692
208.09	2,967	4,422	36	255	7,680	7,585	−95	0.987630

(continued)

Table 10.7 (continued)

	Columns adjusted, first iteration							
Census tract	Hispanic	NH-White	NH-Black	NH-Other	Sum of ethnic groups[a]	Census tract control	Difference[b]	Row factor[c]
Sum of census tracts[d]	10,041	24,380	447	1,676			**−1**	
SRA control	10,040	24,380	447	1,676				
Difference[e]	−1	0	0	0	**−1**			
Column factor[f]	0.999900	1.000000	1.000000	1.000000				

	Columns adjusted, third iteration							
Census tract	Hispanic	NH-White	NH-Black	NH-Other	Sum of ethnic groups[a]	Census tract control	Difference[b]	Row factor[c]
208.01	1,052	3,658	35	233	4,978	4,979	1	1.000201
208.05	1,114	2,017	77	125	3,333	3,333	0	1.000000
208.06	2,551	3,110	122	332	6,115	6,114	−1	0.999836
208.07	584	1,593	5	126	2,308	2,308	0	1.000000
208.08	1,794	9,648	172	609	12,223	12,224	1	1.000082
208.09	2,944	4,355	36	252	7,587	7,585	−2	0.999736
Sum of census tracts[d]	10,039	24,381	447	1,677			**−1**	
SRA control	10,040	24,380	447	1,676				
Difference[e]	1	−1	0	−1	**−1**			
Column factor[f]	1.000100	0.999959	1.000000	0.999404				

[a]Sum of the population projections in each ethnic group
[b]Census tract control − sum of the population projections in each ethnic group
[c]Census tract control / sum of the population estimates each ethnic group
[d]Sum of the population projections in each census tract
[e]SRA control − sum of the population projections in each census tract
[f]SRA control / sum of the population projections in each census tract

After the first set of adjustments all the row adjustment factors are 1.0 (or very close to 1.0), indicating convergence to the projections of total population for the census tracts. In addition, the total amount of adjustment now required is close to zero (−**2**) for both the sum of racial/ethnic groups and the sum of census tracts). However, the sum of census tract projections for each racial/ethnic group is still inconsistent with the control totals. In fact, the column adjustment factor for non-Hispanic other races has changed from a value less than 1.0 in Panel 1 to a value of greater than 1.0 in Panel 2.

The third panel ("Columns Adjusted, First Iteration") shows the population projections by racial/ethnic group for each census tract after we adjusted them to match the column control totals. For example, the adjusted Hispanic population in census tract 208.01 is now:

$$(956)\ (1.087875) = 1,040$$

All of the column adjustment factors are now 1.0 (or very close to 1.0), indicating convergence to the population projections by racial/ethnic group for the SRA, but the column adjustments have made the sum of the racial/ethnic group projections for census tracts inconsistent with the total population projections for census tracts. However, the differences are much smaller than they were before; none is greater than 177. This comparison shows that significant convergence to both marginal totals has occurred after only one full iteration of the process.

The last panel of Table 10.7 ("Columns Adjusted, Third Iteration") shows the results after three full iterations. As is evident from this panel, the census tract projections by race/ethnicity have now converged (within rounding error) to both the SRA control totals for each racial/ethnic group and to the population control totals for each census tract.

The IP method—and other controlling methods—may not always come as close to the independent (control) projections as the examples shown here. Raising the level of demographic detail and reducing the geographic scale can cause multiplicative adjustment routines to lose their efficiency because the computations may not change the original values as much as is needed to produce complete convergence. For example, integer values less than 5 will not change unless the adjustment is at least 10% (e.g., 5 times 1.09 still equals 5 after rounding to the nearest integer). If this occurs with enough frequency, controlling falls short of its intended objective. This problem can be alleviated (but not solved completely) by using decimal points instead of integers.

To handle circumstances where multiplicative adjustments are not adequate, alternative mathematical controlling strategies have been developed (e.g., San Diego Association of Governments 1998). These involve probabilistic assignment routines and/or iterative schemes that apply small additive adjustments to the uncontrolled observations. Private data vendors do some of the most innovative work in this area but—for obvious reasons—are reluctant to reveal their trade secrets.

10.3 Providing Additional Temporal and Age Detail

Many applications of the cohort-component method use 5-year age groups and produce projections in 5-year intervals. With a launch year of 2010, for example, projections might be made for 2015, 2020, 2025, and 2030 for the age groups 0–4, 5–9, 10–14, . . ., 85+. What if a projection is needed for 2017 instead of 2020 or a projection for ages 15–17 rather than 15–19? In this section we discuss some methods for disaggregating projections by age and interpolating between target years.

The methods discussed in this section are somewhat imprecise. They do not reflect all the subtleties in the age distribution or pick up temporal growth patterns as well as a single-year cohort-component model. They are very useful, however, because they offer a reasonable and cost-effective alternative to the application of a single-year projection model.

10.3.1 Adding Temporal Detail

The creation of projections for intermediate years can be viewed as an interpolation problem. Suppose that our goal is to develop annual projections for the years between two target years. We describe three approaches to interpolation that do not require data beyond what is directly available from the projection model itself. The first assumes that change occurs linearly over the projection interval, which means that numerical changes are the same for each year in the interval. The second assumes that change occurs geometrically over the projection interval, which means that percent changes are the same for each year in the interval. The third uses osculatory methods that incorporate information from several different projection intervals.

We illustrate each approach using a set of population projections by age for San Diego County (San Diego Association of Governments 2011), focusing on annual interpolations between target years 2025 and 2030. Because they exhibit sharply contrasting growth patterns, we use a different age group to illustrate each approach. Although the interpolations illustrated here are for 1-year intervals, the same methods could be used for other intervals as well (e.g., quarters, months). These methods can be used for constructing interpolations not only for age groups, but for total population, specific racial or ethnic groups, and other variables as well.

10.3.1.1 Linear Interpolation

For linear interpolation, the average annual numeric change between launch year l and target year t is calculated as the difference between the populations at the beginning and end of the interval, divided by the number of years in the interval:

$$\mathrm{AANC} = (\mathrm{P_t} - \mathrm{P_l})/\mathrm{z}$$

where $AANC$ is the average annual numeric change; P_t is the population in the target year; P_l is the population in the launch year; and z is the number of years in the projection interval. It should be noted that P_l refers to the start of any projection interval. For example, a projection for 2015 is made using 2010 as the initial launch year; the 2015 projection then serves as the launch year for a 2020 projection.

We can compute the average annual change for total population or for any demographic characteristic (e.g., an age group). The annual change is successively added (or subtracted, in the case of a population loss) to the population at the beginning of the projection interval to obtain a projection for the intermediate years:

$$\mathrm{P}_{\mathrm{l+w}} = \mathrm{P}_{\mathrm{l}} + (\mathrm{AANC})\ (\mathrm{w})$$

where *w* is the number of years between the beginning of the projection interval and the intermediate year. To illustrate linear interpolation, we develop annual population projections for the population aged 0–4:

$$\begin{gathered}\text{Population in 2020} : 240,110\\ \text{Population in 2025} : 245,972\\ \text{AANC} : (245,972 - 240,110)/5 = 1,172\\ \text{2021 projection} :\ \ 249,110 + 1,172 = 241,282\\ \text{2022 projection} :\ \ 249,110 + (1,172)\ (2) = 242,454\\ \text{2023 projection} :\ \ 249,110 + (1,172)\ (3) = 243,626\\ \text{2024 projection} :\ \ 249,110 + (1,172)\ (4) = 244,798\end{gathered}$$

10.3.1.2 Geometric Interpolation

Geometric interpolation assumes that the annual percent change is the same for each year in the projection interval. It uses the average annual growth rate to determine an intermediate year projection, based on the geometric formula described in Chap. 2:

$$\mathrm{GF} = (\mathrm{P}_{\mathrm{t}}/\mathrm{P}_{\mathrm{l}})^{(1/\mathrm{z})}$$

GF is a growth factor that represents 1.0 plus the average annual population growth rate over the projection interval. This factor is between 0.0 and 1.0 for population losses and greater than 1.0 for population gains. A growth factor of 1.0 indicates no change in the population. Much like calculating the balance in a bank account using compound interest, the population at the beginning of the projection interval is compounded by the average annual rate of population growth to obtain a projection for the intermediate years:

$$\mathrm{P}_{\mathrm{l+w}} = (\mathrm{P}_{\mathrm{l}})\ (\mathrm{GF}^{\mathrm{w}})$$

To illustrate, we develop annual population projections for population aged 80–84:

$$\begin{gathered}
\text{Population in 2020} : 57,094 \\
\text{Population in 2025} : 69,907 \\
\text{Growth factor} : (69,607/57,094)^{(1/5)} = 1.04132 \\
\text{2021 projection} : (57,094)\ (1.04132) = 59,453 \\
\text{2022 projection} : (57,094)\ (1.04132)^2 = 61,910 \\
\text{2023 projection} : (57,094)\ (1.04132)^3 = 64,468 \\
\text{2024 projection} : (57,094)\ (1.04132)^4 = 67,132
\end{gathered}$$

10.3.1.3 Osculatory Interpolation

The third approach—osculatory interpolation—produces smoother interpolations than either linear or geometric interpolation because it incorporates more information about population changes over time. Specifically, osculatory interpolation methods incorporate information on population change during the time intervals immediately before and after the projection interval, as well as information from the projection interval itself. For example, interpolations for 2020–2025 include information from 2015 to 2020 and 2025–2030 as well as from 2020 to 2025.

A number of different methods can be used to construct osculatory interpolations. All are based on equations that combine two overlapping polynomial functions. Although the construction of these equations is somewhat complex, the application of the coefficients derived from them is not complicated. Judson and Popoff (2004) present coefficients for some of the most commonly used osculatory interpolation methods (i.e., Karup-King, Sprague, Beers Ordinary, and Beers Modified).

To illustrate osculatory interpolation, we use Karup-King coefficients to develop interpolations for each year within a 5-year interval. There are three types of Karup-King coefficients. Middle-interval coefficients are used for most intervals in the projection horizon; they incorporate information from time intervals immediately before and after the projection interval. Last-interval coefficients are used for the final interval in the projection horizon (e.g., 2035–2040 for projections through 2040). They are not as reliable as middle-interval coefficients because they use information from only one side of the projection interval (i.e., the preceding interval). First-interval coefficients are also available, but are seldom needed because historical data are usually available. For example, if the first projection interval were 2010–2015, we could use the 2005 estimates and 2010 census to provide data for the time period immediately preceding the first projection interval.

Using Karup-King middle-interval coefficients, we created annual interpolations for 2021–2024 for the population aged 30–34 (Table 10.8). These coefficients were obtained from Judson and Popoff (2004, Table C-13, Panel A) and are applicable for annual interpolations within 5-year projection horizons or, more generally, between

Table 10.8 Karup-King interpolations between target years 2020 and 2025, population aged 30–34, San Diego County

	2015	2020	2025	2030	
Population[a]	215,026	247,905	260,936	242,920	
	Middle-interval coefficients				
Year	G1 (2015)	G2 (2020)	G3 (2025)	G4 (2030)	
2021	−0.064	0.912	0.168	−0.016	
2022	−0.072	0.696	0.424	−0.048	
2023	−0.048	0.424	0.696	−0.072	
2024	−0.016	0.168	0.912	−0.064	
	Intermediate calculations[b]				
Year	G1 (2015)	G2 (2020)	G3 (2025)	G4 (2030)	Population projection[c]
2021	−13,761.7	226,089.4	43,837.2	−3,886.7	252,278
2022	−15,481.9	172,541.9	110,636.9	−11,660.2	256,037
2023	−10,321.2	105,111.7	181,611.5	−17,490.2	258,912
2024	−3,440.4	41,648.0	237,973.6	−15,546.9	260,634

[a]2050 Regional Growth Forecast. San Diego Association of Governments, Oct. 2011
[b]Coefficient × population in the appropriate year
[c]Sum of the intermediate calculations for each year

any two points at intervals of 0.2. There are four coefficients for each year in the interval for which interpolations are to be made. These coefficients correspond to:

1. Five years before the beginning of the interval (i.e., 2015).
2. The beginning of the interval (i.e., 2020).
3. The end of the interval (i.e., 2025).
4. Five years after the end of the interval (i.e., 2030).

For the intermediate computations we multiply the coefficients by the population projection for the appropriate year. For example, for 2021 the intermediate calculations are:

$$\begin{aligned}(-0.064)\ (215,026) &= -13,761.7\\ (0.912)\ (247,905) &= 226,089.4\\ (0.168)\ (260,936) &= 43,837.2\\ (-0.016)\ (242,920) &= -3,886.7\end{aligned}$$

To obtain the population projection for an intervening year we sum the four intermediate calculations for that year. For 2021, the projection is:

$$-13,761.7 + 226,089.4 + 43,837.2 - 3,886.7 = 252,278$$

Interpolations based on the Karup-King method are essentially weighted averages of projected (or estimated) populations. For each interpolation year, the weights sum to 1.0. For the years defining the beginning and end of the projection interval the weights are directly related to the distance between the interpolation year and the beginning and ending years. That is, the closer the interpolation year is to the projection year, the greater the weight assigned to that projection year. For example, the 2020 population is assigned a weight of 0.912 for the 2021 interpolation; the weight drops to 0.696 for 2022, 0.424 for 2023, and 0.168 for 2024. Conversely, the weight assigned to the 2025 population increases steadily throughout the interval. Interpolations from osculatory methods thus fit more smoothly with population changes observed for earlier and later time periods than do either linear or geometric interpolation methods.

Another osculatory interpolation method that has emerged in recent years is based on cubic splines. Like other osculatory methods, cubic splines fit a piecewise cubic polynomial to a portion of the data, but constrain the relationship of one cubic spline to the next one in the series (Judson and Popoff 2004). We do not provide a detailed description of this method because the computations are more difficult to show than computations for other osculatory methods. However, we constructed a set of cubic spline interpolations using Microsoft Excel and a free add-in developed by SRS1 Software (http://www.srs1software.com). An evaluation of those interpolations—and those produced by the other interpolation methods—is provided in the next section.

10.3.1.4 Evaluation

Which approach to interpolation is best? Linear and geometric methods require the least data and are the simplest to apply. The computations for osculatory interpolation methods are more extensive, require external multipliers, incorporate projections for intervals outside of the interval being interpolated, and may require computer software. However, coefficients for several osculatory interpolation methods are readily available and can be applied fairly easily. We believe the choice of interpolation method should be based not only on computational simplicity, but also on characteristics such as the magnitude, trend, and direction of projected population change.

Figure 10.3 shows projected population change in 5-year intervals from 2015 to 2030 for the three age groups used in our illustrations (0–4, 30–34, and 80–84). The growth patterns suggest which interpolation method (or methods) might be most appropriate for each age group. Linear interpolation seems suitable for ages 0–4 because the projections show relatively constant numeric change in each of the three periods. The steadily increasing numeric changes shown for ages 80–84 suggests the use of geometric interpolation. Finally, osculatory interpolation is likely the best approach when the growth pattern changes direction and has clearly defined turning points, such as shown for ages 30–34.

To judge the suitability of alternative interpolation methods in different population change scenarios, we examined the accuracy of each method for each age group. We measured accuracy by comparing the interpolations with results derived from an independent set of annual projections for 2021, 2022, 2023, and 2024.

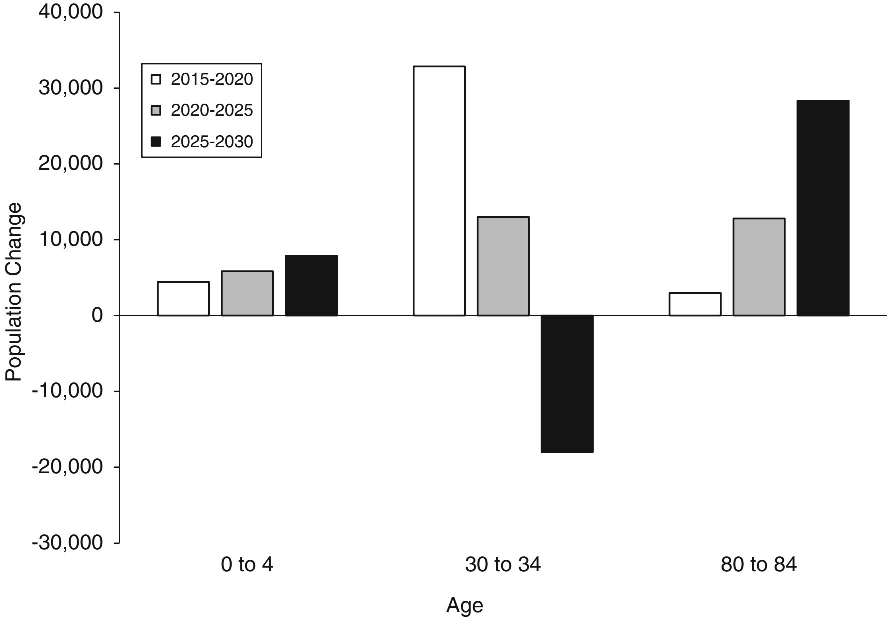

Fig. 10.3 Projected changes in population for selected age groups, San Diego County, 2015–2030

These independent projections were produced using a single-year cohort-component projection model. We call the differences between the interpolations and the projections *errors*, under the assumption that a single-year projection model will provide more reliable projections for the intermediate years than will an interpolation method based on projections of broader age groups. We calculated the mean absolute percent error for the four interpolated years for each interpolation method and each age group.

Figure 10.4 shows the results of these comparisons. They generally support our suggestion that the choice of interpolation method should be based on projected patterns of change. The osculatory methods performed substantially better than the other two methods for both the 30–34 and 80–84 age groups. In particular, neither the linear nor geometric interpolation methods were able to pick up the dramatic shifts in population growth observed for the 30–34 age group. Linear interpolation performed poorly for both the 30–34 and 80–84 age groups, which were characterized by rapidly declining and increasing numeric changes, respectively. Geometric interpolation performed better than linear interpolation for the 80–84 age group, but not as well as the osculatory methods. For ages 0–4, which exhibited an approximately linear growth trend over the three 5-year periods, errors were very low for all four methods.

The osculatory methods produced the lowest errors in two of the three age groups, reflecting the advantage of incorporating information from several time periods into the interpolation procedure. They were substantially more accurate than either the

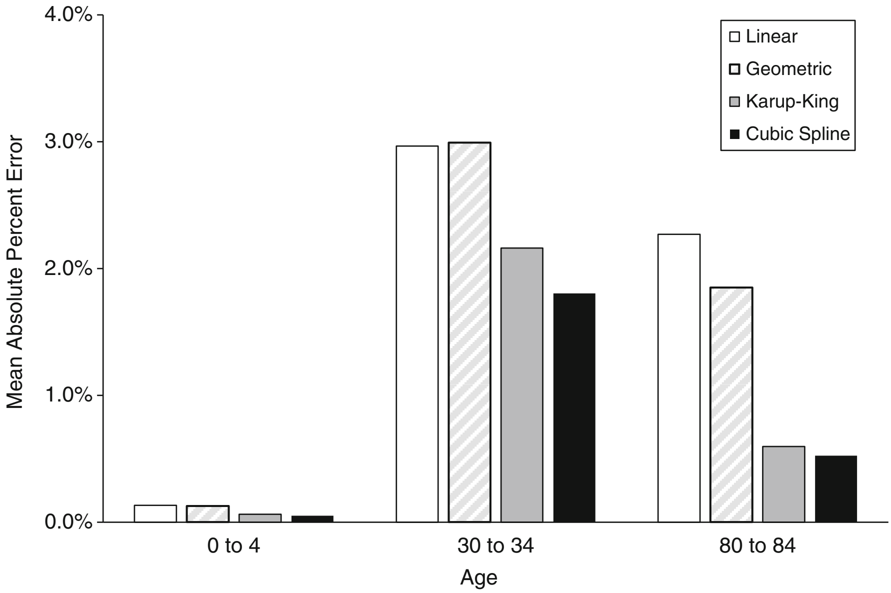

Fig. 10.4 A comparison of interpolation errors for selected age groups, San Diego County, 2021–2025

linear or geometric methods under the scenarios of steadily increasing growth (ages 80–84) and rapidly changing growth patterns (ages 30–34). We believe osculatory methods represent the best approach to interpolation when growth patterns are projected to change rapidly. However, all four methods had similar errors under the scenario of roughly constant numeric increases (ages 0–4). This suggests that simpler methods provide an acceptable alternative to more complex methods when projected population change remains relatively constant over time.

The methods described above used a period approach for interpolating between projected age groups (e.g., population aged 20–24 in both 2010 and 2020). A cohort approach also could be used (e.g., population aged 20–24 in 2010 and 30–34 in 2020). A cohort approach is more complicated when using grouped data, but may be better at picking up subtleties in the age distribution, especially when interpolating to years within a longer projection interval (e.g., 10 years instead of 5 years). Descriptions of the cohort approach to interpolation may be found in Bryan (2004) and Shryock and Siegel (1973).

10.3.2 Adding Age Detail

The division of broad age groups into smaller age groups can also be viewed as an interpolation problem. It can be achieved using a number of different methods (Judson and Popoff 2004). We discuss three of the most commonly used: rectangular distribution, osculatory interpolation, and historical patterns. The data required by the rectangular distribution and osculatory methods are available from the projections themselves, whereas the historical patterns method requires additional data. To illustrate these methods, we use 2020 projections for ages 15–19 in El Dorado County, California (State of California 2007). El Dorado is a small, mostly rural county near Lake Tahoe in northeast California.

10.3.2.1 Rectangular Distribution

The simplest method for splitting age groups into smaller categories is to apply a rectangular distribution, which assumes that all the smaller groups (e.g., 1-year age groups) have identical shares of the larger group (e.g., 5-year age group). The numbers in each of the smaller groups can be computed by dividing the population of the larger group by the number of subdivisions desired. For example, the projected population aged 15–19 in El Dorado County in 2020 is 12,991. Using the rectangular distribution method, the population within each 1-year age group is computed as:

$$12,991/5 = 2,598$$

It is simple to create a projection for any age or age group within the 15–19 group by multiplying the 1-year number by the width of the age group desired. For example, a population projection for the population aged 18–19 is computed as:

$$(2,598)\ (2) = 5,196$$

10.3.2.2 Osculatory Interpolation

Osculatory interpolation methods for splitting age groups are similar to those described above for interpolating between target years. However, instead of using data for earlier and later time periods, they use data for younger and older age groups. This allows these methods to pick up some of the effects of past fertility and migration patterns on the overall age structure of the population. Judson and Popoff (2004) present coefficients for several osculatory methods that can be used for splitting age groups. Although the concepts are similar, these are *not* the same as the coefficients used for interpolating between two points in time.

Again, we use Karup-King coefficients to illustrate the use of osculatory interpolation. Several sets of coefficients are available, corresponding to different sizes of age groups (e.g., dividing 10-year age groups into 5-year age groups or 1-year age groups). We use the coefficients needed for dividing 5-year age groups into 1-year age groups.

To illustrate this method, we divide the projected population aged 15–19 in El Dorado County in 2020 into single years of age (Table 10.9). As before, we use middle-interval coefficients. First- and last-interval coefficients have been

Table 10.9 Karup-King single age interpolation, population aged 15–19, El Dorado County, 2020

	10–14	15–19	20–24	
Population[a]	12,449	12,991	11,780	
	Middle-interval coefficients			
Age	G1 (10–14)	G2 (15–19)	G3 (20–24)	
15	0.064	0.152	−0.016	
16	0.008	0.224	−0.032	
17	−0.024	0.248	−0.024	
18	−0.032	0.224	0.008	
19	−0.016	0.152	0.064	
	Intermediate calculations[b]			
Age	G1 (10–14)	G2 (15–19)	G3 (20–24)	Population projection[c]
15	796.7	1,974.6	−188.5	2,583
16	99.6	2,910.0	−377.0	2,633
17	−298.8	3,221.8	−282.7	2,640
18	−398.4	2,910.0	94.2	2,606
19	−199.2	1,974.6	753.9	2,529

[a]State of California, Department of Finance, population projections for California and its counties 2000–2050, by age, gender and race/ethnicity, Sacramento, CA, July 2007
[b]Coefficient × population in the appropriate 5-year age group
[c]Sum of the intermediate calculations for each age

constructed for the youngest (0–4) and oldest (85+) age groups, but interpolations for these groups are not as reliable as interpolations for other groups because they use information from only one side of the relevant age group (Judson and Popoff 2004).

There are three coefficients for each single year of age: one corresponding to the group to be subdivided (15–19), one corresponding to the next younger group (10–14), and one corresponding to the next older group (20–24). For the intermediate calculations we multiply the coefficients by the population in the appropriate 5-year age group. For example, the intermediate calculations for age 18 are:

$$
\begin{aligned}
(-0.032)\,(12,449) &= -398.4 \\
(0.224)\,(12,991) &= 2,910.0 \\
(0.008)\,(11,780) &= 94.2
\end{aligned}
$$

To obtain the projection for each year of age we sum the three intermediate calculations for each age group. For age 18, the projection is:

$$-398.4 + 2,910.0 + 94.2 = 2,606$$

Karup-King and other osculatory interpolation methods are self-normalizing in the sense that the sum of the projections for the single years of age within an age group sum to the projected population of that group (within rounding error).

This occurs because the weights for the age group to be interpolated (e.g., 15–19) sum to 1.0 and the weights for the immediately younger and older age groups sum to zero.

10.3.2.3 Historical Patterns

The rectangular distribution method assumes that all the smaller groups within a larger group have identical shares of the larger group's population. Osculatory methods assume that the population distribution across broader age groups provides a reasonable representation of the distribution *within* a given age group. If the distribution within an age group has a special or distinctive pattern, however, these methods will not yield reasonable results. For example, places with a college or university will have a relatively large number of persons aged 18–19, throwing off the typical distribution within the 15–19 age group. Rural areas may have relatively *small* proportions of persons aged 18–19 because of high rates of out-migration in that age group. Atypical distributions within other age broad groups may occur in places with large military installations, prisons, high levels of retiree migration, and so forth.

One way to handle these situations—or, for that matter, the entire disaggregation process—is to split broader age groups into smaller groups using historical data on the distribution of persons within those groups. We call this the *historical patterns* method. It requires the compilation and integration of data beyond that needed by the other two methods. The additional effort required to collect those data depends on the number of age groups involved, the number of historical time points used, and the number of strata involved (e.g., two sexes and five racial/ethnic groups).

Despite the additional data requirements, the application of the historical patterns method is not complicated. To illustrate this method, we split El Dorado County's projected population 15–19 in 2020 into two subgroups: 15–17 and 18–19. We describe two approaches based on the number of persons aged 18–19 as a share of the number aged 15–19. In the last two censuses (2000 and 2010), these shares were 0.3441 and 0.3587, respectively. The projection for the population aged 15–17 is calculated as a residual by subtracting the projection of the population aged 18–19 from the projection of the population aged 15–19.

The first approach assumes that the most recent population share does not change; this is the constant share method described in Chap. 8. For example, we can project the population aged 18–19 in 2020 by multiplying the 2010 share by the 2020 projection for the population aged 15–19:

$$(12,991)\ (0.3587) = 4,660$$

The second approach is based on the continuation of recent trends in population shares; this is the SHIFT method described in Chap. 8. In our example, the share increased between 2000 and 2010. This approach assumes that the share will increase by the same amount between 2010 and 2020. To project the 2020 share,

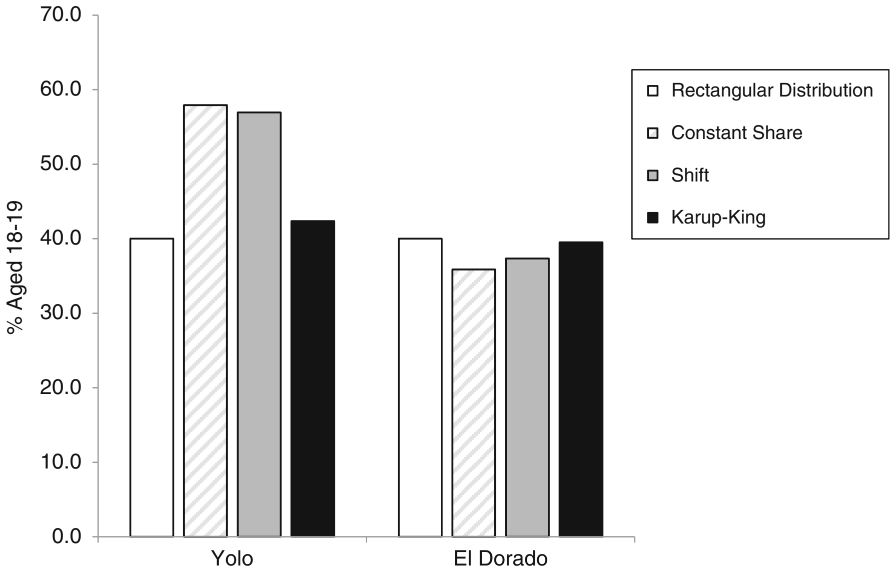

Fig. 10.5 Projections of the population aged 18–19 as a proportion of the population aged 15–19, El Dorado and Yolo counties, 2020

we simply subtract the 2000 share from the 2010 share and add that result to the 2010 share. We then apply the projected share to the projected population aged 15–19 in 2020:

$$0.3587 + (0.3587 - 0.3440) = 0.3734$$
$$(12{,}991)\ (0.3734) = 4{,}851$$

As is true for all projection methods, one must be careful when specifying the assumptions used in the historical patterns method. The most widely used assumption is that the share from the most recent census will remain constant. This assumption avoids the error of extrapolating short-term changes that prove to be temporary. The SHIFT method will be appropriate if there is evidence that recent changes in shares reflect a long-term trend. The historical patterns method is particularly useful for places with institutional populations that retain a constant age structure year after year (e.g., colleges and universities).

10.3.2.4 Evaluation

Figure 10.5 shows the projected population aged 18–19 as a proportion of the projected population aged 15–19 in 2020 for El Dorado and Yolo Counties. As noted above, El Dorado County is a small rural county near Lake Tahoe, whereas Yolo County is a medium-sized county in north central California and is home to the University of California, Davis.

Although the projections generated by the four alternative methods in El Dorado County differ from each other, the differences are relatively modest: All four methods have between 35% and 40% of the population aged 15–19 in the 18–19 age group. The two historical methods have the lowest proportions, which may be reflecting the out-migration teenagers after they graduate from high school. For Yolo County, projections from the historical patterns methods differ substantially from projections from the Karup-King and rectangular distribution methods. Because of the university, Yolo County has a much higher proportion of persons aged 18–19 than most counties. In places like Yolo County, the rectangular proportions and osculatory methods do not provide satisfactory results. These examples emphasize the importance of considering the unique characteristics of an area before deciding on an interpolation strategy (or, more generally, before deciding on the entire projection strategy).

10.4 Conclusions

There are circumstances in which the projection methods described in this book cannot be applied in a simple, straightforward way. Missing or inaccurate data, complicated population dynamics, and unique characteristics or events sometimes mean a basic projection model must be adjusted before reasonable projections can be made. In addition, even reasonable projections sometimes need to be modified to make them as useful as possible.

In this chapter, we described several adjustment procedures for dealing with the impact of special populations; for controlling one set of projections to another; and for adding temporal and age detail. These procedures will not solve every problem that might be encountered, of course, but they will help the analyst deal with some of the special circumstances that confound the production of population projections.

Projections could also be adjusted to account for the impact of census enumeration errors. However, enumeration errors at the national level have declined steadily since 1950 (except for a small increase between 1980 and 1990) and were very close to zero in both 2000 and 2010 (Brown et al. 2010; U.S. Census Bureau 2012). Given that enumeration errors are generally small and vary considerably from place to place—and that estimates of errors for local areas themselves contain a substantial amount of error—we do not believe it is necessary to adjust population projections for census enumeration errors except in very unusual circumstances.

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Chapter 11
Related Projections

The previous chapters focused on projections of total population and the basic demographic characteristics of age, sex, and race/ethnicity. Such projections are useful for many purposes, but there are circumstances in which projections of households, school enrollment, health, disability, income, poverty, employment, labor force, and other population-related variables are needed for purposes of planning, budgeting, policy analysis, and program administration. These projections are related to population projections in that they are strongly affected by population size and demographic composition, but they are influenced by other factors as well.

In this chapter, we describe two methods for making projections of socioeconomic characteristics, health characteristics, and a variety of population subgroups (e.g., persons in prison or enrolled in government benefits programs). One method derives these projections from population projections by age (and sometimes by sex, race, and ethnicity as well) and the other employs cohort-change ratios similar to those described in Chap. 7. We illustrate the application of these methods using projections of school enrollment, disability, labor force, and households. For simplicity, we refer to these as "population-related" projections to distinguish them from projections of basic demographic characteristics (i.e., age, sex, and race/ethnicity).

11.1 Concepts, Definitions, Methods

Socioeconomic and health characteristics possess a feature that distinguishes them from strictly demographic characteristics; namely, they are "achieved" rather than "ascribed." Ascribed characteristics such as age, sex, and race/ethnicity are largely set at birth, while achieved characteristics such as educational attainment, marital status, and labor force status change over time (Stark 2007). This distinction is not totally clear-cut, however, because a person's sex or gender classification can be

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DOI 10.1007/978-94-007-7551-0_11,

altered and his/her racial and ethnic identity may vary according to the prevailing social context (Alba and Islam 2009; Kaneshiro et al. 2011).

Because they can change substantially over time, population-related characteristics are generally more difficult to project accurately than strictly demographic characteristics. Fortunately, many achieved characteristics are closely related to ascribed characteristics through their association with stages of the life cycle. For example, entering kindergarten, graduating from high school, getting married, giving birth, entering and exiting the labor force, and suffering a disability are activities associated with population aging. Projections of a population's age structure (and, to a lesser extent, its sex and race/ethnicity structure) thus provide a basis for projecting population-related characteristics.

We describe two basic methods for constructing population-related projections (for further discussion, see George et al. (2004) and Siegel (2002, Chap. 11). Both have small data requirements and are relatively easy to apply, making them particularly useful for small-area projections. The first is the *participation-ratio method* (also known as the participation-rate method, prevalence-ratio method, and incidence-rate method), in which projections of population-related variables are derived from population projections through the use of ratios. The second is the *cohort-progression method*, in which projections of population-related variables are developed by surviving forward persons with the characteristics of interest. Although more complex methods can be used—and offer several advantages in some circumstances—we believe the methods described here will be adequate for many purposes.

11.1.1 Participation-Ratio Method

In this method, current and historical data are used to construct ratios reflecting the proportion of the population having the characteristic of interest (e.g., enrolled in school). Ratios are typically constructed separately for each age group and are often broken down by sex, race, and ethnicity as well. They can be projected by holding them constant, extrapolating recent trends, tying them to projected changes in other places, using structural models, or relying on expert judgment. The projected ratios are then applied to population projections by age (and often by sex, race, and ethnicity) to obtain projections of the characteristic of interest. There are three steps in applying this method:

1. Calculate launch year participation ratios: $PR_{c,d,l} = P_{c,d,l} / P_{d,l}$
2. Project those ratios into the future: $PR_{c,d,l+z}$
3. Apply the projected ratios to the projected population:
   $P_{c,d,l+z} = (PR_{c,d,l+z})\,(P_{d,l+z})$

where *PR* is the participation ratio; *P* is the population; *c* is the characteristic of interest (e.g., enrolled in school); *d* is the demographic group (e.g., an age-sex cohort); *l* is the launch year; and *z* is the length of projection interval. These steps are followed for each demographic group and for each interval over the projection horizon, providing a complete set of projections for the characteristic of interest.

11.1.2 Cohort-Progression Method

In this method, the population with the characteristic of interest is projected directly rather than as a proportion of the larger population. There are two steps in applying this method. First, a cohort-progression ratio is constructed for each demographic category using data from the base year and the launch year (e.g., 2000 and 2010). Second, the population with the characteristic of interest for each demographic group is projected by multiplying this ratio by the relevant launch year population:

1. Calculate cohort-progression ratios: $CPR_{c,d,l} = P_{c,d,l}/P_{c,d-z,l-z}$
2. Apply those ratios to the launch year population: $P_{c,d+z,l+z} = (CPR_{c,d,l})\ (P_{c,d,l})$

The terms in these equations are the same as those used for the participation-ratio method, except that *z* now refers to the interval between the base year and the launch year as well as the projection interval. This interval can be of any length (e.g., a year or a decade), but must be the same for both the projection interval and the base period. Ratios are constructed for each demographic category and are applied for each interval over the projection horizon. The cohort-progression method is essentially the same as the Hamilton-Perry method discussed in Chaps. 6 and 7, the only difference being that the cohort-change ratios now refer to the population with a particular characteristic rather than to the population as a whole.

11.1.3 Other Considerations

What issues must an analyst address when preparing population-related projections? Perhaps the most fundamental is obtaining the necessary data. Both the participation-ratio and cohort-progression methods require age-specific data on the variable of interest, and perhaps sex- and race/ethnicity-specific data as well. These data are often available from administrative records (e.g., enrollment data from school district administrators) or surveys (e.g., income data from the ACS). Clearly, the availability of reliable data is essential for the production of reasonable projections.

The participation-ratio method requires population data for constructing ratios and a set of population projections to which the projected ratios can be applied. Population data from the decennial census or post-censal estimates can generally be used as denominators in the ratios. If reliable data for either the numerator or denominator are not available for a particular area, ratios from similar areas can be used as proxies (e.g., county ratios used for census tract projections). If independently produced population projections are not available, they can be constructed using the methods described in previous chapters.

The participation-ratio method requires that ratios be projected into the future. As noted previously, this can be done in a number of different ways. Making reasonable choices regarding future ratios is crucial to the reliability of the projections but is largely a subjective process. Thorough knowledge of historical trends and the factors affecting the variable of interest is essential. In some circumstances, it may be advisable to consult an expert in the field before making these choices and to apply several alternative assumptions in order to provide a range of projections.

For the cohort-progression method, projections of the variable of interest are based solely on its previous growth patterns, with no consideration of the factors affecting that variable or overall population trends. This may be a risky approach for some types of projections, especially when the projections extend very far into the future. For example, if younger cohorts do not follow the same labor force participation patterns as older cohorts—perhaps by entering the labor force at an older age or retiring at a younger age—the cohort-progression method will produce inaccurate forecasts of the labor force. The analyst must decide whether the future changes implied by the cohort-progression method are reasonable, based on his/her knowledge of the variable of interest and overall population trends.

Reasonable projections of population-related variables can be made only if the analyst makes reasonable choices regarding participation and cohort-progression ratios. Thorough knowledge of the population-related variables—and how they are related to the stages of the life cycle—are essential (Martins et al. 2012, pp. 83–98; Modigliani 1970; O'Rand and Krecker 1990). The following illustrations focus on the mechanics of applying the participation-ratio and cohort-progression methods, but the reader is reminded that the quality of the data and the validity of the underlying assumptions are at least as important as the projection methods themselves.

11.2 Illustrations of Population-Related Projections

11.2.1 School Enrollment

School enrollment projections are critical for determining future needs for educational facilities, equipment, and staffing. We start with an illustration of the *participation-ratio method*, projecting the number of students enrolled in public schools in Shelby County, Tennessee in the 2019–2020 school year.

The first step in the projection process is to calculate participation ratios in the launch year, using 2009–2010 enrollment data provided by school administrators and population data from the 2010 census. Grades were organized into three groups: pre-kindergarten and kindergarten; grades 1–8; and grades 9–12. Ratios of the enrollments for these groups to their corresponding age groups were computed using 0–4 for pre-kindergarten and kindergarten, 5–14 for grades 1–8, and 15–19 for grades 9–12. Although the age groups do not precisely match the ages of children by grade, this lack of correspondence will generally not be a problem as long as the ratios are applied consistently. We use broad grade groups in this

Table 11.1 School enrollment projections by grade group, Shelby County, Tennessee, 2019–2020

Grade group	2010 Population[a]	2009–2010 Enrollment	Ratio	2020 Population[b]	2019–2020 Enrollment[c]
Kindergarten[d]	66,659	14,237	0.21358	69,711	14,889
1–8	134,250	95,860	0.71404	135,665	96,870
9–12	71,799	47,414	0.66037	63,666	42,043
Total	272,708	157,511		269,042	153,802

Sources: National Center for Education Statistics (http://nces.ed.gov/ccd/bat/), U.S. Census Bureau, 2010 census

[a]Ages 0–4 for kindergarten, 5–14 for grades 1–8, and 15–19 for grades 9–12

[b]Projection derived using the Hamilton-Perry Method

[c]2010 ratio × 2020 population

[d]Includes pre-kindergarten

example, but more detailed projections could be made if they were needed and if the necessary data were available (e.g., single-year participation ratios based on enrollment in individual grades).

The 2010 participation ratio for pre-kindergarten and kindergarten was 0.21358. This was calculated by dividing the number of children enrolled in pre-kindergarten and kindergarten (14,237) by the number of children aged 0–4 (66,659). For grades 1–8 and 9–12, the ratios were 0.71404 and 0.66037, respectively. These participation ratios are not closer to 1.0 because the number of grades in each grade group was smaller than the number of years in the corresponding age group and some children living in Shelby County were home schooled or attended private schools.

The second step in the projection process is to project the participation ratios ahead 10 years. Based on an analysis of previous trends, it was assumed that the ratios would be the same in 2019–2020 as they were in 2009–2010. If there had been evidence that these ratios were changing in a predictable manner, alternative assumptions could have been developed. As a final step, the participation ratios are applied to a set of 2020 projections for the corresponding age groups. The input data, participation ratios, and projections for 2019–2020 are shown in Table 11.1. The number of kindergarteners and pre-kindergarteners and students in grades 1–8 is projected to increase slightly over the 10-year period while the number of students in grades 9–12 is projected to decline.

Our second illustration uses the *cohort-progression method*, which is similar to the Hamilton-Perry method but focuses on the number of students in each grade rather than the number of persons in each age group. When used for school enrollment projections, the cohort-progression method is often called the "grade-progression method." Grade-progression ratios (GPR) are calculated by dividing the number of students in a given grade in a given year by the number of students in the prior grade in the prior year. The cohort-progression method is particularly useful for developing short-range projections by grade.

Because data on the number of pre-kindergarten children are generally not available, an alternative procedure must be used for projecting the number of kindergarteners. One approach is to divide the number of kindergarteners in a given year by the sum of first and second graders in the same year and apply this ratio to the projected number of first and second graders in the target year. Another

Table 11.2 School enrollment projections by grade, Santa Barbara County, California School District, 2012

Grade	2010	2011	GPR[a]	2012[b]
K	5,498	5,512	0.50671[c]	5,600[d]
Grade 1	5,373	5,533	1.00637	5,547
Grade 2	5,060	5,345	0.99479	5,504
Grade 3	4,827	5,001	0.98834	5,283
Grade 4	4,860	4,871	1.00912	5,047
Grade 5	5,020	4,852	0.99835	4,863
Grade 6	4,834	5,021	1.00020	4,853
Grade 7	5,046	4,833	0.99979	5,020
Grade 8	4,833	5,032	0.99723	4,820
Grade 9	5,097	4,998	1.03414	5,204
Grade 10	5,125	5,068	0.99431	4,970
Grade 11	5,196	5,042	0.98380	4,986
Grade 12	5,278	5,222	1.00500	5,067
Total	66,047	66,330		66,764

Source: California Department of Education, http://dq.cde.ca.gov/dataquest
[a]2011 enrollment grade x / 2010 enrollment grade $x - 1$ (except for grade K)
[b]Progression ratio grade $x \times$ 2011 enrollment grade $x - 1$ (except for grade K)
[c]2011 enrollment grade K / 2011 enrollment grades 1 and 2
[d]Progression ratio grade K $\times$ 2012 enrollment grades 1 and 2

approach is to calculate the ratio of kindergartners in a given year to births 5 years earlier and multiply this ratio by the number of births 5 years prior to the target year. Either approach is acceptable for most short-range projections.

We illustrate the grade-progression method using public school data from Santa Barbara, California. We use fall enrollment data in 2010 and 2011 to project fall enrollment by grade in 2012. For example, there were 5,060 students in grade 2 in 2010 and 5,001 students in grade 3 in 2011, yielding a grade progression ratio of 0.98834. By multiplying this ratio by the number of second graders in 2011 (5,345), we project that there will be 5,283 third graders in 2012. This procedure is applied to all grades between K and 11 to project the number of students in grades 1 through 12 in the following year. The results are shown in Table 11.2.

We project the number of kindergarteners using a ratio of kindergarteners to the number of students in grades 1 and 2. In 2011, there were 5,512 students in kindergarten and 10,878 students in grades 1 and 2, yielding a ratio of 0.50671. By multiplying this ratio by the projected number of students in grades 1 and 2 in 2012 (11,051), we project that there will be 5,600 kindergarteners in 2012.

11.2.2 Disability

The older population of the United States is large and growing rapidly. There were 35 million persons aged 65 and older in 2000, representing 12% of the total

Table 11.3 Projections of the U.S. population with mobility limitations by age and sex, 2050

	Males				
	2000			2050	
Age[a]	Population	With limitation	Ratio	Population	With limitation[b]
<35	60,949,682	1,121,581	0.01840	92,751,167	1,706,621
35–44	22,795,548	1,244,430	0.05459	24,899,130	1,359,244
45–54	18,432,972	1,644,908	0.08924	22,902,724	2,043,839
55–64	11,582,552	1,814,774	0.15668	22,152,960	3,470,926
65–74	8,245,839	1,794,954	0.21768	18,294,495	3,982,346
75–84	4,815,313	1,507,354	0.31303	12,774,881	3,998,921
85+	1,306,660	618,657	0.47346	8,188,551	3,876,951
Total	128,128,566	9,746,658	0.07607	201,963,908	20,438,848[c]
	Females				
	2000			2050	
Age[a]	Population	With limitation	Ratio	Population	With limitation[b]
<35	58,747,107	1,024,801	0.01744	89,183,536	1,555,361
35–44	23,124,437	1,303,179	0.05636	24,574,905	1,385,042
45–54	19,172,397	1,812,554	0.09454	22,931,099	2,167,906
55–64	12,590,270	2,039,293	0.16197	22,654,996	3,669,430
65–74	9,989,648	2,313,961	0.23164	19,602,520	4,540,728
75–84	7,577,579	2,760,742	0.36433	15,773,852	5,746,887
85+	3,045,737	1,852,722	0.60830	13,432,080	8,170,734
Total	134,247,175	13,107,252	0.09764	208,152,988	27,236,088[c]

Source: Smith et al. (2008) and unpublished data
[a]Data for population 5 years and older
[b]2000 ratio × 2050 population
[c]Sum of the age groups

population. This population is projected to reach almost 84 million by 2050, or 21% of the total population (U.S. Census Bureau 2012b). Since the prevalence of many disabilities rises with age, the aging of the population is likely to bring substantial increases in the number of disabled persons.

Smith et al. (2008) used the participation-ratio method to project the number of persons with a particular type of disability; namely, mobility limitations. First, they constructed mobility limitation ratios by age and sex using population data from the 2000 census and data on mobility limitations from 2000 Public Use Microdata Sample (PUMS) files. These ratios are shown in Table 11.3.

Then, they developed three scenarios regarding changes in those ratios between 2000 and 2050. Under the medium scenario, ratios were projected to remain constant through 2050. Under the low and high scenarios, they were projected to fall or rise by 5% per decade, respectively. They applied the projected ratios to projections of the U.S. population by age and sex. The results for the medium scenario are shown in the last column of Table 11.3. Under this scenario, the number of persons with mobility limitations was projected to grow by 109% between 2000 and 2050; under the low and high scenarios, it was projected to grow by 59% and 163%, respectively (not shown here).

Table 11.4 Labor force projections by age, King County, Washington, 2020

	2010			U.S. LFPR		2020		
Age	Population[a]	Labor force	LFPR[b]	2010	2020	LFPR[c]	Population	Labor force[d]
16–19	94,455	31,571	0.334	0.349	0.265	0.254	92,914	23,600
20–24	128,842	96,905	0.752	0.714	0.659	0.694	140,398	97,436
25–44	607,121	522,387	0.860	0.827	0.816	0.849	617,791	524,505
45–54	290,298	244,759	0.843	0.812	0.808	0.839	286,869	240,683
55–64	227,541	164,848	0.724	0.649	0.688	0.768	267,971	205,802
65–74	112,002	31,658	0.283	0.257	0.310	0.341	187,378	63,896
75+	93,760	5,423	0.058	0.074	0.100	0.078	113,662	8,866
Total	1,554,019	1,097,551	0.706	0.647	0.625	0.682	1,706,983	1,164,788[e]

Sources: U.S. Census Bureau, 2010 census and 2010 1-year American Community Survey, State of Washington Forecasting Division, 2012, http://www.ofm.wa.gov/pop/gma/projections12/GMA_2012_county_pop_projections.pdf

[a]Civilian non-institutional population

[b]Labor force / population

[c]2010 LFPR $\times$ (US LFPR 2020 / US LFPR 2010)

[d]2020 LFPR $\times$ 2020 population

[e]Sum of the age groups

The participation-ratio methodology can be used for making a wide variety of projections related to health and disability status (Arterburn et al. 2004; Singer and Manton 1998). Assumptions regarding future changes in prevalence rates are critical to the validity of those projections, of course, making knowledge of the variable of interest essential. Given the differences of opinion often found among experts, it may be advisable to construct projections based on several alternative sets of assumptions.

11.2.3 Labor Force

Projections of the number and characteristics of persons in the labor force are critical to many types of long-range economic planning. The Bureau of Labor Statistics (BLS) uses the participation-ratio method to project the labor force in the United States. These projections are made by applying labor force participation ratios (LFPR) by age, sex, race, and ethnicity (developed by the BLS) to population projections developed by the U.S. Census Bureau (Toossi 2012). The same method can be used for labor force projections at the state and local level. We illustrate this method using data for King County, Washington to project changes in the overall labor force by age between 2010 and 2020 (see Table 11.4).

Three steps are required. First, LFPRs for King County in 2010 are calculated for each age group by dividing the number of persons in the labor force by the population in the age group. For example, there were 128,842 persons aged 20–24 in 2010, of whom 96,905 were in the labor force, yielding a LFPR of 0.752.

Second, county-level LFPRs are projected into the future by assuming that they would change at the same rate as national LFPRs (as projected by the BLS). For example, the national LFPR for the 20–24 age group was projected to fall from 0.714 in 2010 to 0.659 in 2020, a decline of 7.7%. Applying this decline to the King County LFPR of 0.752 in 2010 yields a projected LFPR of 0.694 in 2020. LFPRs are projected to decline for the four youngest age groups and to increase for the three oldest groups. Again, we note that there are a number of ways to project participation ratios into the future.

Third, the projected LFPRs are applied to population projections by age. The population and labor force projections are shown in the last two columns of Table 11.4. For example, the projected population aged 20–24 is 140,398 in 2020. Applying a projected LFPR of 0.694 yields a labor force projection of 97,436 for this age group. The total population of King County is projected to increase by 9.8% between 2010 and 2020, while the labor force is projected to increase by only 6.1%.

11.2.4 Households

According to Census Bureau definitions, a household consists of all persons who occupy a housing unit (U.S. Census Bureau 2012a). A householder is the person (or one of the people) in whose name the housing unit is owned or rented (householders were formerly called “household heads”). Because the number of householders is equal to the number of households, the methods used for projecting socioeconomic and health characteristics can also be used to project households. Household projections are important because they are closely related to the demand for housing and to a whole host of consumer goods and services (Martins et al. 2012).

When it is used to project households, the participation-ratio method is often called the “headship-rate” or “householder-ratio” method. To illustrate this method, we return to Shelby County, Tennessee. Using age-specific data for 2000 and 2010, we project the number of households in 2020 (see Table 11.5). Again, there are three steps in the projection process.

The first is to calculate householder ratios in 2000 and 2010 by dividing the number of householders in each age group by the total population of that group. For example, there were 18,157 householders aged 15–24 and 138,249 persons aged 15–24 in 2010, yielding a householder ratio of 0.13134. Ratios are calculated for each age group up to age 75+.

The second step is to project those ratios to 2020. This could be done by holding them constant, extrapolating past trends, basing them on changes projected for other populations, or tying them to projected changes in marriage patterns and living arrangements. In this illustration, we project householder ratios by extrapolating the changes occurring between 2000 and 2010. For example, the householder

Table 11.5 Household projections by age of householder, Shelby County, Tennessee, 2020

	2000			2010		
Age	Population	Householders	Householder ratio[a]	Population	Householder	Householder ratio[a]
15–24	127,761	20,518	0.16060	138,249	18,157	0.13134
25–34	135,215	66,835	0.49429	129,758	60,084	0.46305
35–44	143,667	78,884	0.54908	124,961	68,048	0.54455
45–54	120,797	71,234	0.58970	132,868	75,677	0.56957
55–64	67,670	42,127	0.62254	105,675	65,091	0.61595
65–74	47,910	31,488	0.65723	52,478	34,722	0.66165
75+	41,671	27,280	0.65465	42,746	22,315	0.52204
Total	684,691	338,366		726,735	344,094	

	2020		
Age	Householder ratio[a,b]	Population[c]	Households[d]
15–24	0.10741	128,447	13,796
25–34	0.43378	140,412	60,908
35–44	0.54006	119,897	64,751
45–54	0.55013	115,568	63,577
55–64	0.60943	115,992	70,689
65–74	0.66610	81,893	54,549
75+	0.41629	46,324	19,284
Total		748,533	347,554

Sources: U.S. Census Bureau, 2000 and 2010 censuses
[a]Householders / population
[b]Assumes that the percent change in the householder ratio from 2000 to 2010 will continue to 2020
[c]Projection derived using the Hamilton-Perry Method
[d]2020 householder ratio × 2020 population

ratio for the 15–24 age group was 0.16060 in 2000 and 0.13134 in 2010, yielding an extrapolated ratio of 0.10741 in 2020.

The third step is to apply the projected householder ratios to the projected population by age in 2020. This is shown in the last two columns of Table 11.5. For example, the projected population aged 15–24 is 128,447 and the projected ratio is 0.10741, yielding a projection of 13,796 households. The total number of households is calculated by adding up the projected households in each age group. Overall, the number of households is projected to grow by 1.0% between 2010 and 2020, compared to an increase of 1.7% between 2000 and 2010.

If desired, projections of housing units (HU) can be derived from projections of households by dividing by the occupancy rate (OR). For example, the occupancy rate for Shelby County was 88.1% in 2010. Assuming that this rate remains constant to 2020, the projected number of housing units can be calculated as:

$$394,499 = 347,554/0.881$$

Housing units for small areas can also be projected directly, using data on historical trends, zoning requirements, the amount of buildable land, and other relevant factors (Population Research Center 2009; Southern California Association of Governments 2013). As noted in Chap. 9, these projections are often tied to urban systems or microsimulation models. Population projections can be derived from these direct projections of housing units by applying the well-known and widely used housing unit method (Swanson and Tayman 2012, Chap. 7):

$$\mathrm{Pop_t} = (\mathrm{HU_t})(\mathrm{OR_t})(\mathrm{PPH_t}) + (\mathrm{GQ_t})$$

where *t* is the target year; *PPH* is the average household size, and *GQ* is the group quarters population.

11.3 Conclusions

The participation-ratio and cohort-progression methods described in this chapter are conceptually simple and relatively easy to apply. More complex methods for projecting households, school enrollment, health status, employment, income, and other population-related variables have also been developed (Lindh and Malmberg 2007; Sweeney and Middleton 2005; Zeng et al. 2006). More complex methods draw on a greater variety of inter-relationships among variables and provide a richer array of detailed characteristics than simpler methods; for some purposes, they will be more useful than the methods described here. However, the methods described here require considerably less data and can be applied more easily than more complex methods; these are important advantages when resources are scarce and time is short. Their relatively small data requirements are particularly important for small-area projections because many types of data are not available for small areas. We believe there are many circumstances in which the methods described here will provide useful projections of population-related variables.

Although the participation-ratio and cohort-progression methods have been widely used, the usefulness of the projections they produce will depend on the validity of their underlying assumptions. The illustrations presented in this chapter depict several different approaches to projecting future participation ratios. In the school enrollment projections, ratios were held constant; in the disability projections, three alternative assumptions regarding future ratios were applied; in the labor force projections, county ratios were assumed to change at the same rate as national ratios; and in the household projections, previous changes in the ratios were extrapolated into the future. Structural models and expert judgment could also be used. Developing reasonable assumptions regarding future participation ratios—or deciding whether the changes implied by applying constant cohort-progression ratios are reasonable—is an important part of the development of any set of population-related projections. Thorough knowledge of historical trends and the factors affecting the variables of interest is essential. Although the participation-ratio and cohort-progression methods are capable of producing reasonably accurate forecasts, there is no guarantee that they will actually do so.

Population-related projections can be used to address a broad array of socioeconomic and health-related issues. The methods described in this chapter have been used to develop caseload forecasts for the Supplemental Nutrition Assistance Program (SNAP) and the Temporary Assistance for Needy Families (TANF) program in Oregon (Vaidya, K., 2012, Senior Demographer, Oregon Office of Economic Analysis. Salem, OR, personal communication); forecasts of the number of people receiving "in-home" disability benefits in Washington (Deschamps, E., 2012, Deputy Director, Washington State Caseload Forecast Council. Olympia, WA, personal communication); long-range forecasts of K-12 school enrollment, also in Washington (Steiger, J., 2012, Director, Washington State Caseload Forecast Council. Olympia, WA, personal communication); forecasts of the number of obese adults in the United States (Arterburn et al. 2004); forecasts of disability rates and Medicare costs in the United States (Bhattacharya et al. 2004); and forecasts of the number of households in France (National Institute of Statistics and Economic Studies 2005). Clearly, population-related projections play an important role in many types of real-world decision making.

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Chapter 12
Evaluating Projections

We have now discussed the four major approaches to making population projections: the cohort-component method, trend extrapolation methods, structural models, and microsimulation models. All these approaches include a variety of models, techniques, assumptions, special adjustments, and types of data that can be used to produce the desired projections. Given all the possibilities, how does one go about choosing the specific models, techniques, assumptions, and data sources to use for a particular set of projections? Is there a single "best" approach, or at least some that are better than others? Are some approaches better under some circumstances, while others are better under other circumstances? How can we even go about answering these questions?

In this chapter we describe a number of criteria that can be used to evaluate population projections. We begin with a discussion of the criteria we believe are most important: provision of necessary detail, face validity, plausibility, costs of production, timeliness, ease of application and explanation, usefulness as an analytical tool, political acceptability, and forecast accuracy. After describing these criteria we consider how they must be balanced against each other when choosing projection methods. We close with an assessment of how different methods stack up according to these criteria. Forecast accuracy is such an important criterion that we devote an entire chapter to its measurement and evaluation (Chap. 13). Further discussion of criteria for evaluating population projections may be found in Ahlburg (1995), Booth (2006), Keilman (1990), Long (1995), and Siegel (2002).

We distinguish between two types of projections. *General-purpose projections* are those produced without reference to a specific use or data user. Examples include projections produced by the Census Bureau for all states in the United States, projections produced by a state demographer for all the counties in his/her state, and projections produced by a private company for all the census tracts in the United States. *Customized projections* are those produced for a particular data user or a specific purpose. Examples include population projections by block group for developing a county's transportation plan, birth projections by market

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area for evaluating a hospital's need for obstetrical services, and school enrollment projections by grade level for evaluating a school district's need for additional facilities.

12.1 Evaluation Criteria

12.1.1 Provision of Necessary Detail

Perhaps the most fundamental criterion for evaluating population projections is whether they provide the level of geographic, demographic, and temporal detail required by the data user. State projections are of little use to someone needing county projections. Projections of total population are of little use to someone needing projections by age and sex. Projections for 2020 are of little use to someone needing projections for 2040.

When projections are made for a specific client or for a particular purpose, it is easy to determine whether they provide the necessary level of detail. In fact, the producer can make sure of this. When general-purpose projections are made by a government agency, university, research institute, or private company, however, it is much more difficult to determine whether they meet user needs. What geographic areas should be covered? What demographic characteristics? What projection intervals and time horizons? It is virtually impossible to meet all user needs with one set of projections because needs vary so much across data users.

12.1.1.1 Geographic Detail

Many data users need population projections for states and counties. These needs can be met fairly easily because the geographic boundaries for states and most counties remain relatively stable over time and many types of data are routinely available at the state and county levels. In addition, the number of states and counties is finite and relatively manageable; there are more than 3,100 counties or county equivalents nationwide, with the largest numbers in Texas (254) and Georgia (159). Most states have fewer than 100 counties or county equivalents.

For subcounty areas, however, the number of potential areas—and even the ways in which those areas might be defined—is virtually endless. Possibilities include cities, census tracts, block groups, blocks, zip code areas, school districts, traffic analysis zones, and many types of market or service areas. Projections that meet the needs for geographic detail for the vast majority of data users would have to be made at the block or even the parcel level. Those projections could then be aggregated to fit the geographic region required by each individual data user. Such a process, of course, would be extremely expensive and fraught with problems of data availability and reliability.

12.1.1.2 Demographic Detail

The need for demographic detail also varies from user to user. Some require only total population numbers while others require breakdowns by age, sex, race, and/or ethnicity. Some need age data in single-year groups; for others, 5- or 10-year groups are sufficient. Some require projections of specific population subgroups such as college students, military personnel, seasonal residents, and persons with disabilities. Others require projections by income, education, occupation, poverty status, or other socioeconomic and demographic characteristics. Again, the potential for variation in user needs is virtually endless.

12.1.1.3 Temporal Detail

By *temporal detail*, we mean the length of the projection horizon and the length of time interval between projection dates. Some data users need projections for 1- or 2-year horizons, some need projections for 5- or 10-year horizons, and a few need projections for horizons stretching 50 years and beyond. Some need projections only in 5- or 10-year intervals, some need annual projections, and a few need quarterly or even monthly projections. The longer the horizon and the shorter the interval, the greater the potential usefulness of a set of projections to a broad range of data users. However, data and techniques that are satisfactory for short-range projections may be unsatisfactory for long-range projections. In addition, data and techniques suitable for projections made in 5- or 10-year intervals may be unsuitable for monthly, quarterly, or annual projections.

12.1.1.4 Meeting User Needs

The needs of the largest number of potential data users can be met (at least theoretically) by making projections that are highly disaggregated by geographic area and demographic characteristic and that cover long time horizons in frequent intervals. Armed with these building blocks, data users can put together projections that cover the specific geographic areas, demographic characteristics, and projection horizons they need. For example, block projections produced at annual intervals 20 years into the future can be added together to provide projections of school districts, traffic analysis zones, or market areas within a county, using whatever demographic categories and time horizons that might be needed.

The greater the degree of disaggregation, however, the greater the data requirements, the lower the reliability of the data, the higher the costs of production, and the lower the expected degree of forecast accuracy for each detailed category. These are strong incentives *against* the production of highly disaggregated projections. As a result, most producers of general-purpose projections provide projections that cover a limited number of geographic areas, demographic categories, and time horizons.

The Census Bureau, for example, makes projections by age, sex, race, and Hispanic origin for the nation as a whole. It also makes projections for states on an irregular basis (one, two, or three times each decade). The Census Bureau has never made projections for counties but did make one set of projections for metropolitan areas (U.S. Census Bureau 1969). Many state demographic agencies make projections by age and sex (and sometimes by race and/or Hispanic origin) for counties within their state, but few make projections for subcounty areas. Some local and regional governments make projections (with widely varying degrees of demographic detail) for census tracts, traffic analysis zones, or other subcounty areas within their boundaries. Several private companies make projections for all counties in the United States, with a few breaking them down into a variety of subcounty areas.

Projection horizons typically vary by level of geography. For example, horizons are often longer for national projections than for state and local projections. Although some projections are made in 1-year intervals, 5-year intervals are the most frequently used. As discussed in Chap. 10, interpolation procedures can be used to transform projections made in 5- or 10-year intervals into projections for intervening years.

The most basic criterion for judging the potential usefulness of a set of population projections, then, is whether those projections provide the level of geographic, demographic, and temporal detail needed for any particular purpose. If the projections cannot at least come close to meeting those requirements, they will not be very useful regardless of how well they do with respect to other criteria. General-purpose projections will be able to meet the needs of many data users for many purposes, but some projects will require that projections be created specifically for the purposes at hand.

12.1.2 Face Validity

By *face validity*, we mean the extent to which a projection uses the best methods for a particular purpose, is based on reliable data and reasonable assumptions, and accounts for relevant factors. Because of the effects of population and geographic size, evaluating face validity is considerably more complex and time-consuming for small areas (e.g., census tracts) than for large areas (e.g., states).

12.1.2.1 Choice of Methods

The face validity of a method depends primarily on the purposes for which the projections will be used. All the methods discussed in this book can be used for projections of total population; even simple methods will be acceptable for many purposes. For projections by age group, the analyst must account for shifts in age structure over time; this implies the use of some variant of the cohort-component method. For projections of the components of growth, the model must distinguish among the effects of fertility, mortality, and migration. Projections incorporating interactions among economic, land-use, transportation, and demographic variables require the use of structural models and projections for individual persons and households require the use of microsimulation models.

Does the degree of complexity or sophistication affect the face validity of a projection method? We believe that it does, but only to the extent to which complexity or sophistication is required to accomplish the purposes for which the projections will be used. For projections used strictly as forecasts of total population, neither a sophisticated structural model nor a complex multi-regional model is necessarily better than a simple extrapolation of recent trends. For projections tracing out the implications of alternative economic, land-use, transportation, or demographic scenarios, however, structural models or relatively complex cohort-component models will be required. The face validity of a particular model or technique cannot be generalized; rather, it is conditional upon the specific purposes for which the projections will be used.

12.1.2.2 Data and Assumptions

Face validity is affected by the quality of the data and assumptions used to create the projections. Although they are not perfect, data from complete censuses are generally quite accurate, especially for areas with large populations. Data from sample surveys such as the American Community Survey (ACS) are less reliable, especially for small areas. Postcensal population estimates are less accurate than decennial census data, especially for small areas and places that are growing or declining rapidly. Vital statistics data are highly accurate for states and counties, less accurate for subcounty areas (if they are even available). The quality of data used in structural and microsimulation models varies by type and geographic area. An important part of assessing the face validity of population projections, then, is evaluating the quality of the input data and making adjustments when necessary to correct for apparent errors.

The timeliness of input data may also affect face validity. Demographic data vary in terms of time lags and frequency of release. Decennial census data are available only once every 10 years, whereas birth, death, and other vital statistics data are available annually. Migration data based on IRS records are also available annually, but with roughly a 2-year time lag. ACS data are released annually but are based on 1-, 3-, or 5-year time periods, depending on the area's population size. For small areas, then, ACS estimates (including migration estimates) reflect 5 years of accumulated data rather than data from a single year.

The application of any projection method requires that certain assumptions be made. Cohort-component projections require assumptions regarding future fertility, mortality, and migration rates. Structural and microsimulation models require assumptions regarding the form of the model, the choice of independent variables, and the estimation of parameters. Even simple extrapolation methods are based on assumptions regarding the length of the base period and adjustments for special events and potential growth constraints. Assessing the "reasonableness" of the underlying assumptions is an important aspect of evaluating face validity.

12.1.2.3 Accounting for Relevant Factors

Face validity is also determined by the extent to which the projection methodology accounts for the impact of factors affecting population change. Drawing on the discussion by Murdock et al. (1991), we suggest that the following factors may have an impact on small-area projections:

1. Physical features, such as the size of an area and the prevalence of potentially growth-constraining factors such as flood plains, lakes, mountains, and environmentally protected areas.
2. Location characteristics, such as distances from recreational areas, major employers, and shopping centers.
3. Land-use patterns and policies, including population density, land-use plans, and zoning or regulatory restrictions.
4. Housing characteristics, such as housing density, household size, and housing units by type (single family, multifamily, mobile home).
5. Transportation characteristics, such as current and likely future access to major highways, airports, railways, and other modes of transportation.
6. Socioeconomic characteristics, such as income, education, occupation, and poverty status.
7. Population characteristics, such as population size, rate of change, distribution within the area, and composition (e.g., age, sex, race, ethnicity).
8. Demographic processes (mortality, fertility, migration).
9. Special populations, such as persons residing in prisons, college dormitories, and military barracks.

Several examples illustrate how these factors might be accounted for. Suppose that county projections are made in 5-year intervals from 2010 to 2030, based on historical data from 2005 to 2010. Suppose further that a state prison housing 1,000 inmates was built in a small county in 2007. If the addition of those inmates is not explicitly accounted for in the base data, the projections would in effect be assuming that 1,000 inmates will be added to the population every 5 years between 2010 and 2030. This will probably not be a reasonable assumption. This effect can be accounted for by taking the inmates out of the base data, making the projections based on the remaining data, and adding independent projections of inmates as a final step in the projection process (see Chap. 10 for further details).

As a second example, suppose that projections for census tracts (CT) are made based on population trends from 2000 to 2010. Suppose further that CT 123 grew very rapidly during that period, from 1,000 residents in 2000 to 5,000 in 2010. If no adjustments were made, that tract would be projected to continue growing rapidly in future decades. This will not be a realistic assumption if no more developable residential land is available in CT 123. Situations like this can be dealt with by introducing growth constraints based on factors such as the availability of vacant land, zoning restrictions, and topographical features.

We are not suggesting that all the factors mentioned above must be accounted for in every set of projections, of course. In many instances, reliable, up-to-date data will not be available. Even if data are available, our understanding of all the processes at work is generally insufficient to permit us to improve on the results of a basic (i.e., unadjusted) projection model. In addition, for states and large counties the effects of some factors will be swamped by the effects of other factors, or the effects of a particular factor in one area will be offset by opposite effects in another area.

We do suggest, however, that these factors be considered at some point during the projection process and that adjustments be made when necessary and feasible. Such adjustments are especially important for projections of subcounty areas because the impact of these factors is largest in small areas. These adjustments cannot guarantee that accurate forecasts will be made, but at least they can reduce one potential source of error.

12.1.3 Plausibility

By *plausibility*, we mean the extent to which a projection is consistent with historical trends, with the assumptions inherent to the model, and with projections for other areas. Plausibility is closely related to face validity; in fact, the two may be thought of as opposite sides of the same coin. Face validity focuses on the inputs into the projection process, whereas plausibility focuses on the outcomes. If a projection is not based on valid data, techniques, and assumptions, it is not likely to provide plausible results.

Plausibility, of course, is a subjective concept. Just as beauty is in the eye of the beholder, so too is plausibility. A trend that appears eminently plausible to one observer may seem totally implausible to another. How can plausibility be evaluated?

There are a number of ways. One is to compare numerical tables summarizing historical and projected values of key variables. For example, suppose that we want to evaluate a set of county projections. We could construct a table showing the average annual change in total population projected for each county for future time periods (e.g., 2010–2015, 2015–2020...) and compare those changes with the changes observed during several historical periods (e.g., 2000–2005 and 2005–2010). We could construct another table comparing the age, sex, and race distributions projected for future years (e.g., 2020 and 2030) with those observed in the past (e.g., 2000 and 2010). Are the projections consistent with the underlying assumptions? Are projected changes consistent with those observed in the past? If not, what are the reasons for the differences? Is one of the assumptions invalid? Have some special circumstances been overlooked? Were errors made while entering data or writing computer programs? Answering questions like these provides one type of "plausibility check."

Plausibility can also be evaluated by comparing projections for one area with those for another. For example, trends for one county can be compared with trends for another county or for the state as a whole. Are the changes in total population size projected for one area consistent with those projected for another? What about projected changes in the age, sex, and race distribution? Can reasonable explanations be given for any diverging trends?

Checking for consistency between projected and historical values and comparing projections for one area with those for another requires a substantial investment of time and effort, but has a potentially large pay-off. Given their subjective nature, however, plausibility checks must be viewed as suggestive rather than conclusive. They provide hints and clues, but cannot "prove" that one set of projections is better than another. In particular, relying too much on comparisons with past trends might cause the analyst to miss the beginning of a new trend (see Box 12.1).

Box 12.1 Plausibility and Assumption Drag

Assumption drag is "the continued use of assumptions long after their validity has been contradicted by the data" (Ascher 1978, p. 53). Assumption drag is a common problem in forecasting and may be caused by several factors. First is the socialization of experts, determined by their education, training, and association with other experts. The "received wisdom" in any field is not often questioned. Second, if recent data seem to contradict longstanding assumptions, they are often viewed as temporary deviations from trends rather than as changes in the trends themselves. Third, there are often delays in the collection and dissemination of data, leading to substantial lags between the point at which trends start to change and the point at which those changes are finally incorporated into forecasting models.

Assumption drag means that projections that are consistent with past population trends may not provide the best forecasts of future population change. Analysts must consider this possibility when evaluating the plausibility of population projections, especially projections used as forecasts. All objective projection methods—even cohort-component and structural models—are extrapolations of one type or another. The critical question is, how can we tell when the model's underlying trends have started (or will start) to change? This is the most difficult question in population forecasting (or any other type of forecasting, for that matter).

12.1.4 Costs of Production

The costs of production for a set of population projections are determined primarily by labor costs. A well-made projection requires that a great deal of time must be spent considering all relevant details; collecting, verifying, and cleaning up input data; putting together a projection model; and evaluating the plausibility of the results. Other costs (e.g., computer hardware and software, purchases of proprietary data) are small in comparison.

Very little research has focused on the costs of constructing population projections. Just how high are those costs and how do they vary by method, level of geographic and demographic detail, and frequency of application? Logic and personal experience suggest that costs increase with the degree of methodological complexity, the level of geographic and demographic detail provided, and the attention paid to special populations and unique events. However, costs can be expected to decline with the number of times a specific application is repeated; it takes more time to produce a set of projections for the first time than to repeat the process additional times.

Can economies of scale reduce the costs of production? That is, can projections for a large number of places be made for a lower average cost than projections for a small number of places? One study reported that producing a set of cohort-component projections for counties required about 2,000 person-hours in Ohio and 1,000 person-hours in Washington (Swanson and Tayman 1995). Since Ohio had about twice as many counties as Washington (88 compared to 39), these results suggest that economies of scale had little impact on the costs of production. If projections are made simply by feeding data into a projection model and spitting out the results, economies of scale will have a large impact on the costs of production. If attention is paid to the reliability of the input data, the potential impact of local characteristics, and the plausibility of the projection results, however, the benefits of economies of scale are likely to be small.

Further research on the costs of production would be very helpful. Other things being equal, lower costs are preferable to higher costs. Other things, however, are rarely equal. Trade-offs must be made between costs of production and other attributes of population projections. Assessing the costs of production—and their relationship to other projection attributes—is central to the evaluation process.

12.1.5 Timeliness

There are several aspects to the concept of timeliness. We covered one in the discussion of face validity; namely, the frequency with which input data are released and the time lag between the reference date and the date when the data actually become available. Another is the frequency with which projections are produced. The Census Bureau produced two or three sets of state projections each decade between 1950 and 2000, but produced only one set between 2000 and 2010. Demographers in some states produce state and county projections on an annual basis, some produce them every other year, and some produce them at irregular intervals (Judson 1997). Frequent revisions are particularly important for small areas because of the volatility in their growth patterns.

A third aspect of timeliness is the amount of time needed to construct the projections. This is determined by the scope of the project and by the number of analysts available to work on it. Production time takes on particular importance when a set of customized projections is created for a specific client. The client (who may be someone within the same organization as the analyst) may require that the projections be completed within a short (perhaps unreasonably short) period. In some circumstances, production time is a major factor determining the choice of projection methods.

12.1.6 Ease of Application and Explanation

Ease of application is determined by the amount of time and the level of expertise needed to collect, verify, and adjust the input data; develop a projection model; and generate the desired projections. This criterion will be particularly important for analysts with limited training or expertise in the production of population projections or who face severe time or budget constraints.

Ease of explanation refers to the extent to which data users can be provided with a clear description of the data sources, assumptions, and techniques used in producing the projections. For some data users, this criterion is irrelevant. They are interested only in the projections themselves, not in how they were produced. Other data users, however, can truly evaluate (and properly use) a set of projections only if they understand how those projections were made. Indeed, some may have little or no use for projections based on unknown methods or "black box" models. For those data users, the clearer and more complete the description of the methodology, the more valuable the projections.

12.1.7 Usefulness as an Analytical Tool

Population projections are used most frequently as forecasts, or as predictions of future trends in population size, distribution, and composition. However—as noted in Chap. 1—they are also used to analyze the components of growth, trace out the effects of recent trends or specific changes in those trends, demonstrate the sensitivity of population growth to particular variables or assumptions, and relate changes in demographic variables to changes in economic or other variables. In some circumstances the extent to which projections can be used for these purposes is the main determinant of their usefulness.

Projections can answer a wide variety of questions. What impact would a 10% decline in the birth rate have on future population size and composition? What would be the impact of the elimination of a particular cause of death? How would the expansion of a major employer affect a county's migration rates? What would the continuation of current growth rates mean for future water consumption? How is population aging likely to affect the inflow and outflow of funds in public or private pension systems? The answers to these and similar questions can teach us a great deal about the determinants and consequences of population growth and demographic change.

12.1.8 Political Acceptability

Population projections are never produced in a vacuum. They are influenced by the context in which they are produced and by the perspectives of those who produce (or approve) them. Cohort-component models are based on assumptions regarding future mortality, fertility, and migration rates. Structural and microsimulation models are based on decisions regarding which variables to include and how to estimate the parameters. Even simple extrapolation models involve choices regarding data and technique(s), length of base period, special populations, unique events, and potential growth constraints. All projections are political statements in the sense that they are based on a particular view of the determinants of population change.

The political acceptability of population projections can be interpreted in several ways. One is the extent to which projections made by technical analysts are acceptable to the persons or agencies sponsoring the projections. Sponsoring parties are often government agencies, but can be businesses or non-governmental organizations as well. These parties may have strong vested interests in the projected numbers and may seek to influence those numbers. Another interpretation of political acceptability is the extent to which projections are accepted as unbiased, reasonable, or authoritative by data users and members of the general public. This will be determined by the reputation and track record of the analyst or agency producing the projections. Both interpretations are important, but we focus primarily on the first in the present discussion.

As Moen (1984) pointed out, population growth and distribution are deeply imbedded in politics. A county government might want to show that the county has a rapidly growing population and a healthy economy in order to attract new businesses and residents. An environmental group might want to show that there is a need for growth restrictions or more stringent pollution regulations. A real estate developer might want to show that there is a need for additional housing and roads. A school board or parents group might want to show that there is a need for another elementary school. In these examples, projections are meant to play an active rather than a passive role; that is, they are meant to *influence* future growth rather than simply chart the likely course of that growth.

Political considerations can create problems for analysts constructing population projections. Dennis (1987) described a case in which three governmental agencies were given the task of constructing projections of vehicle miles traveled in the Denver metropolitan area. It was anticipated that these projections would have a major impact on the funding and planning activities of each agency. In the early stages of the projection process the projections were based on parameter estimates developed jointly by the technical staffs of the three agencies. These estimates were developed in a "veil of ignorance," or without knowing their impact on the final projections. This approach helps minimize bias and ensure objectivity. However, an impasse developed when the results were found to be politically unacceptable to one of the agencies. Eventually, the impasse was broken only after decision-making power was passed to a different governmental agency, with the final decision based on political considerations rather than technical merit.

Tayman and Swanson (1996) cited an example from Detroit, where the technical staff of the planning department produced a set of projections showing a population loss between 1980 and 1990. Those projections were consistent with previous trends, but were viewed as unacceptable by political decision makers; they were revised upward to show a population increase. This revision was based strictly on political considerations; all the technical factors pointed to a population decline. (The original projections were later found to have been considerably more accurate than the revised projections).

McKibben (1996) described a situation in which political opposition was successfully overcome. A small, largely rural county in Indiana had been experiencing steady declines in school enrollment for years. The school board formulated a long-term building and consolidation plan that called for the closing of three small elementary schools located in the rural areas of the county. This plan was strongly opposed by a sizable segment of the rural population and by several members of the school board, who believed the widely publicized "echo of the baby boom" would produce enough enrollment growth to justify renovating those schools and keeping them open. A group of consultants was hired by the school board to make 10-year projections of school enrollment by grade. Their projections showed further declines in school enrollment and were initially met with widespread disbelief and fervent opposition. However, by providing a clear description of the data, techniques, and assumptions used in developing the projections, the consultants were able to convince most of the skeptics that future declines in school enrollment were more likely than future increases.

The potential conflict between political and technical considerations raises a number of difficult questions. What role should political considerations play in the projection process? How can the (perhaps conflicting) viewpoints of a variety of interest groups be incorporated? At what point does the incorporation of political considerations cause the projections (and the analyst) to lose credibility? What is the analyst to do when the person who signs his/her paycheck wants to change the projections for purely political reasons?

In our experience, major conflicts between political and technical considerations occur relatively rarely. When they do occur, however, they create thorny ethical and procedural dilemmas. In these circumstances, balancing political acceptability with technical legitimacy may be the most difficult part of the projection process. In the long run, we believe the negative consequences of producing unreasonable, politically-motivated projections far outweigh whatever short-run benefits they might provide.

Political influences are not uniformly negative, however. There are circumstances in which such influences have a *positive* impact on the validity and usefulness of population projections. This can occur, for example, when the projections are produced as part of a comprehensive urban plan. Tayman (1996) described the interplay between the construction of population projections and the development of a growth management strategy in the San Diego metropolitan area. This strategy incorporated policies related to housing, public transportation, commuting, employment, government services, environmental considerations, and alternative land uses. The development of several sets of hypothetical projections allowed public officials to observe the potential effects of different policies and choose the policies expected to be most beneficial for the county. The projections ultimately adopted were the ones consistent with the policies that were to be implemented.

The Tayman study illustrates an "active" approach to population forecasting. Under this approach, political decision makers first decide which future outcomes are the most desirable and then design policies to achieve those outcomes. If the policies prove to be successful, projections consistent with those policies are more realistic than projections that ignore the political context in which they are made. In circumstances like these, incorporating the influence of political considerations improves forecast accuracy and enhances the overall usefulness of the projections.

As we have shown, political factors can have either a positive or negative impact on the validity and usefulness of population projections. When evaluating projections, then, data users must be aware of the context in which they were made. Who made the projections? Why were they made? What roles were they expected to play? Did the producers have a vested interest in the projection results? Did they provide a clear description of the methodology and a convincing explanation for using particular methods and making particular assumptions? The answers to these questions will provide important information for judging the validity of the projections.

12.1.9 Forecast Accuracy

The final criterion for evaluating population projections is forecast accuracy. For many data users this is the most important criterion, in demography and many other fields as well (Booth 2006; Siegel 2002; Yokum and Armstrong 1995). To briefly summarize the empirical evidence, we can say that forecast errors are generally larger for small places than large places; are generally larger for places with very high or negative growth rates than for places with moderate, positive growth rates;

generally increase with the length of the projection horizon; and vary from one launch year to another. The degree of complexity or sophistication of the methodology, however, has no consistent impact on forecast accuracy, at least for projections of total population. Given its importance, we take an in-depth look at forecast accuracy in the next chapter.

12.2 A Balancing Act

All the criteria discussed above are potentially important for choosing the data, techniques, and assumptions that will be used in constructing a set of population projections or for evaluating a set produced by someone else. The relative importance of each criterion, however, varies according to the purposes for which the projections will be used.

The provision of necessary detail is essential for all purposes. If data for the relevant geographic areas, demographic categories, and time periods are not available, the projections will not be very useful. Face validity, plausibility, and timeliness would also seem to be almost universally important; exceptions might be when projections are used simply to illustrate the outcomes of hypothetical scenarios or to push a particular political agenda. Ease of application and costs of production generally do not matter to the data user, but are important to the producer. In fact, these criteria may drive the choice of projection methods when time is limited or budgets are tight. Ease of explanation is unimportant for some data users, critical for others. Political acceptability and analytical usefulness are essential in some circumstances, irrelevant in others. Forecast accuracy may be the most important criterion when projections are used to guide decision making, but is irrelevant when projections are used for simulations or as political propaganda. Indeed, there are circumstances in which planning and intervention may be intended to *prevent* projections from providing accurate forecasts (Isserman 1984).

Choosing the relevant criteria for evaluating a set of projections is a balancing act. Some criteria may be much more important than others and decisions based on one criterion may be inconsistent with decisions based on another. Choices must be made regarding which criteria are most important for a particular set of projections and—when they conflict with each other—which to rank ahead of the other. An optimal projection strategy can be chosen only after weighing the relative importance of each of the evaluation criteria.

12.3 Comparing Methods

Once the relevant evaluation criteria have been chosen, a second type of balancing act occurs as the specific data, methods, procedures, and assumptions used to create the projections are chosen. How do various projection methods stack up according

Table 12.1 Rating projection methods

Evaluation criteria	Simple extrapolation[a]	Complex extrapolation	Cohort-component	Structural/microsim
Geographic detail	****	***	***	***
Demographic detail	*	*	****	****
Temporal detail	-	-	-	-
Face validity	-	-	-	-
Plausibility	-	-	-	-
Cost of production	****	***	**	*
Timeliness	****	***	**	*
Ease of application	****	***	**	*
Ease of explanation	****	**	***	*
Usefulness as analytical tool	*	*	***	****
Political acceptability	-	-	-	-
Forecast accuracy	-	-	-	-

[a]Includes simple and ratio methods
Notation:
****Top ranking
***Second ranking
**Third ranking
*Lowest ranking
-Cannot generalize

to the criteria discussed in this chapter? Table 12.1 summarizes our views regarding the characteristics of the projection methods covered in this book. These rankings are somewhat imprecise because of the potential variability in the ways each method can be applied (e.g., the cohort-component method can be applied using simplified Hamilton-Perry procedures or complex multi-regional models). However, they will give the reader a quick overview of the strengths and weaknesses of the different approaches to constructing population projections.

12.3.1 Provision of Detail

12.3.1.1 Geographic Detail

Trend extrapolation methods have the smallest data requirements of all the methods that can be used for projecting total population. The simplest methods require data from only one or two points in time; more complex methods (e.g., time series models) require data from a number of points in time. Since total population data are readily available (or can be developed) for many different levels of geography and for many different points in time, trend extrapolation methods perform very well in terms of their ability to provide projections for a wide variety of geographic areas, including very small areas.

Cohort-component models do not perform quite as well in this regard. They require mortality, fertility, and migration data, as well as population data by age, sex, and perhaps other characteristics as well. Structural and microsimulation models require historical and projected data on the independent variables. These data are often unavailable or of questionable reliability for subcounty areas. However, the Hamilton-Perry method, urban systems models, and microsimulation models have all been applied to very small geographic areas, showing that data availability is not an insurmountable obstacle. Adjustments may have to be made, but cohort-component and structural models can be used for projections covering a wide variety of geographic areas.

12.3.1.2 Demographic Detail

One of the major advantages of the cohort-component method is that it can provide projections by age, sex, race, and other population characteristics. Structural models can also be used for projections of population characteristics, but are generally used in conjunction with a cohort-component model. Microsimulation models provide very detailed projections of demographic characteristics for individual households and persons. In terms of providing projections of demographic characteristics, then, cohort-component, structural, and microsimulation models perform very well.

Trend extrapolation methods do not perform nearly as well in this regard. They are generally used only for projections of total population or for projecting birth, death, or migration rates; consequently, they generally provide no projections of demographic detail. Could this shortcoming be overcome? Could trend extrapolation methods be applied to subgroups of the population, rather than to the population as a whole? For groups *not* differentiated by age (e.g., females, blacks, Hispanics), it may be reasonable to apply trend extrapolation methods because people generally do not change from one group to another (e.g., female to male, black to white). We are aware of several instances in which trend extrapolation methods have been used in this manner (Leach 1981; Smith and Rayer 2012) and we believe these methods may be useful for projections of race, ethnicity, and perhaps other demographic characteristics for small areas (see Chap. 8). For age projections, however, some type of cohort approach must be used. Trend extrapolation methods applied to specific age groups are not likely to provide acceptable results (Long 1995).

12.3.1.3 Temporal Detail

Trend extrapolation, cohort-component, structural, and microsimulation models are about equal in their ability to produce projections covering specific intervals and time horizons. Some methods that are acceptable for short projection horizons, however, may not be valid for long projection horizons. Chap. 13 discusses why this might be true.

12.3.2 Face Validity and Plausibility

Many of the factors affecting face validity are the same for trend extrapolation, cohort-component, structural, and microsimulation models. All four approaches require that attention be paid to the quality of the input data, to the reasonableness of the assumptions regarding future growth, and to factors such as the physical features of an area, potential growth constraints, and the impact of special populations or unique events. However, face validity is also affected by the purposes for which the projections will be used. All four approaches can provide valid projections of total population, but some type of cohort model must be used for projections of age groups. Structural models must be used for projections incorporating interactions between demographic and other variables, and microsimulation models must be used for projection of individual households and persons. The face validity of a projection method cannot be properly judged without considering the purposes for which the projections will be used.

It is also impossible to generalize regarding the plausibility of trend extrapolation, cohort-component, structural, and microsimulation models. All four are capable of producing either plausible or implausible results, depending on the particular techniques and assumptions employed. For example, the extrapolation of recent growth rates may provide plausible 20-year projections for a county that has been growing by 1% per year, but implausible projections for a county that has been growing by 10% per year. Similarly, the specific assumptions used for mortality, fertility, and migration rates will determine the plausibility of cohort-component projections. The plausibility of projections from structural and microsimulation models will be determined by the structure of the models themselves and the nature of the assumptions regarding future values of the independent variables and other parameters. For all four approaches, plausibility can be evaluated only after comparing projected trends with those observed in the past and those projected for other areas.

12.3.3 Costs and Timeliness

Costs of production—which are determined primarily by labor costs—vary tremendously by projection method. Simple extrapolation methods (including ratio methods) have the smallest data requirements and take the least time to apply. They are the least expensive of all the projection methods. More complex extrapolation methods have larger data requirements and take more time to apply, but are still relatively inexpensive. Cohort-component methods require considerably more time for model development and data collection than trend extrapolation methods. Structural and microsimulation models are also very time-intensive, often requiring a large investment in data collection, model building, and testing. Urban systems and microsimulation models are particularly expensive to develop and implement.

Raising the level of methodological complexity and sophistication is likely to raise the level of expertise needed to produce a set of projections. Since persons with higher skill levels can command higher wages than persons with lower skill levels, this is likely to lead to higher costs as well. Incorporating the potential impact of special populations, unique area-specific events, and potential growth constraints adds considerably to the costs of production, regardless of the methodology employed.

There are several aspects to the concept of timeliness. It can refer to how up-to-date the input data are, the frequency with which projections are produced, or the amount of time required by the production process. Trend extrapolation methods perform better than cohort-component, structural, and microsimulation models on all three of these aspects. Due to their small data requirements and relatively simple mathematical structures, trend extrapolation methods can generally incorporate more recent data, be applied more frequently, and be produced in less time than either cohort-component or structural models. Specific applications of cohort-component, structural, and microsimulation models differ considerably from each other, depending on the level of complexity and degree of sophistication employed. In general, the simpler the method, the more timely the projection is likely to be.

12.3.4 Ease of Application and Explanation

Simple extrapolation methods are the easiest to apply and to explain to data users because they have the simplest mathematical forms, the smallest data requirements, and the least amount of disaggregation. More complex extrapolation methods are more difficult to apply and to describe clearly. The cohort-component method is also more difficult to apply because of its large data requirements and complex set of inter-relationships. Although the basic concepts underlying this method can be explained easily, a full description of all the data sources, techniques, and assumptions requires a lengthy discussion. Structural and microsimulation models are the most difficult to apply and to explain clearly in terms of their technical details, especially when they involve large numbers of simultaneously determined equations and detailed parameters. Interpreting projection results is fairly simple for extrapolation and cohort-component models, but can be difficult for structural and microsimulation models.

12.3.5 Usefulness as an Analytical Tool

Population projections are often used to trace out the implications of alternate demographic scenarios, evaluate the impact of changes in economic conditions, and conduct other types of analyses. They can also be used as teaching tools to demonstrate these effects to students, government officials, business leaders, and the general public. How do various projection methods stack up according to this criterion?

Simple extrapolation methods are not useful for most analytical purposes. They are not directly related to any theories of population growth, to any variables affecting population growth, or to any of the components of population growth. Complex extrapolation methods are only slightly more useful. The logistic method can be related to a theory of growth in which the population first grows slowly, then enters a period of rapid growth, and eventually levels off (Romanuic 1990). Time series models provide prediction intervals indicating the degree of uncertainty surrounding specific projections (de Beer 1993; Lee 1993; Tayman et al. 2007). For most analytical purposes, however, neither simple nor complex extrapolation methods are very useful.

The cohort-component method, on the other hand, is very useful. It can determine the proportion of population growth caused by each individual component. It can trace out changes in the demographic composition of the population. It can demonstrate the sensitivity of population projections to specific changes in individual components of growth. These analyses raise our understanding of population dynamics and improve our ability to plan for the future.

Structural and microsimulation models are even more useful. Models can be developed investigating the effects of a variety of economic, social, cultural, and other factors affecting fertility, mortality, migration, or total population change. These models can be constructed to cover both the determinants and the consequences of population growth and demographic change. They can be used to create population projections that are consistent with a variety of economic, land use, and transportation projections. Regardless of their forecasting capabilities, structural and microsimulation models are extremely useful for analytical purposes.

12.3.6 Political Acceptability

It is impossible to generalize regarding the political acceptability of population projection methods. In some instances a method may be unacceptable simply because it cannot produce the type of projections required. For example, simple extrapolation methods will not be acceptable when an inter-related set of economic-demographic projections are needed. In other instances, any method may be politically acceptable if the analyst or agency producing the projections has a good reputation and a proven track record.

Sometimes political acceptability is determined by the outcome of the projection process rather than by the methods employed. From this perspective, any projection method is acceptable as long as it provides the desired results. If it does not provide the desired results, it is not acceptable regardless of its technical merits. Consequently, any projection method may be politically acceptable in some circumstances and unacceptable in others.

One warning about the political acceptability of simple methods should be mentioned. Simplicity is sometimes interpreted as simple-mindedness. The use of simple methods may make the analyst appear to be lazy or incompetent, whereas the use of complex methods may make him/her appear to be diligent, highly skilled, and trustworthy. Perceptions may be more important than reality, especially when projections must be approved by an outside group or when they produce controversial results. In some circumstances, structural and microsimulation models may be more acceptable than other projection methods simply because they take into account the largest number of factors affecting population growth.

12.3.7 Forecast Accuracy

We will provide a detailed discussion of forecast accuracy in the next chapter. To preview that discussion we can say that no single projection method has been found to provide consistently more accurate forecasts of total population than any other method. In specific circumstances, however, some methods tend to perform better than others.

12.4 Conclusions

Evaluating population projections is a two-step process. The first step is to choose the criteria upon which the projections will be evaluated. Potential criteria include the provision of necessary detail, face validity, plausibility, costs of production, timeliness, ease of application and explanation, usefulness as an analytic tool, political acceptability, and forecast accuracy. The choice of criteria will depend on the purposes for which the projections will be used and the constraints imposed on the analyst producing the projections. For any given purpose some criteria may be very important, some may be moderately important, and a few may be completely unimportant.

The second step is to use these criteria to guide the selection of projection methods. Simple extrapolation methods are characterized by timeliness, ease of application and explanation, low costs of production, and applicability to very small areas; however, they cannot provide much demographic detail and have little usefulness as an analytical tool. More complex extrapolation methods share many of these attributes, but typically require more data and modeling expertise.

Cohort-component methods are much more costly and less timely, but are more useful as analytical tools and are capable of providing a rich array of demographic detail. Structural and microsimulation models are the most data-intensive, time-consuming, and costly, but are capable of providing a variety of inter-related projections and offer the greatest analytical usefulness.

Again, we are left with a balancing act. The importance of each criterion must be weighed against the importance of all the others, and the characteristics of each method must be weighed against the characteristics of all the other methods. Typically, costs and timeliness must be traded off against analytical usefulness and richness of geographic and demographic detail. The most fundamental task facing the analyst is to choose the optimal bundle of characteristics based on the resources available and the purposes for which the projections will be used. This choice will guide the analyst through the selection of projection methods, the collection of input data, and all the other steps of the projection process.

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Chapter 13
Forecast Accuracy and Bias

Demographers often claim they are not in the business of predicting the future. To emphasize that point, they typically call their calculations of future population "projections" rather than forecasts or predictions. They frequently produce several sets of projections rather than a single set, often without providing any indication of the relative likelihood of their occurrence. This reluctance to predict is not surprising, given the frequency with which past forecasts have been wide of the mark.

But data users want forecasts, not projections. They want the analyst's views of what will actually happen in the future, not some series of hypothetical scenarios or conditional probabilities. In fact, data users generally interpret projections as forecasts regardless of the analyst's intentions and whatever terminology or disclaimers might be used. A basic fact of life for demographers is that their "projections" become forecasts as soon as they reach the public.

Given the widespread use of population projections as forecasts—and the many planning decisions and funding allocations tied to those projections—it is essential to evaluate the forecast accuracy and bias of the most commonly used projection methods. This chapter provides such an evaluation. We start with a description and discussion of various statistics that can be used to measure forecast accuracy and bias. We then provide an overview of the empirical evidence, focusing on the effects of differences in projection methodology, population size, growth rate, length of base period, length of forecast horizon, and launch year. We also consider the possibility of producing forecasts by combining several projections. We close with a discussion of ways to account for the uncertainty inherent in population projections. Throughout this chapter, we use the terms *projection* and *forecast* interchangeably because we are interpreting projections as if they were meant to be used as forecasts of future population.

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13.1 Measuring Accuracy and Bias

13.1.1 Defining Forecast Error

We define *forecast error* (*E*) as the difference between the population forecast (*F*) for a particular geographic area in a particular target year (*t*) and the actual population (*A*) for the same area and year:

$$E_t = F_t - A_t$$

For example, if the population of a county had been projected to be 55,000 in 2010 and the actual population turned out to be 50,000, the forecast error would be 5,000. If the population had been projected to be 45,000, the forecast error would be −5,000.

Forecast errors are often expressed as percent differences rather than as numeric differences. This specification is useful when measures of relative error rather than numeric error are needed. The use of percent errors (*PE*) is particularly helpful when making comparisons across geographic areas because—without adjustments for population size—errors for places with large populations would swamp the effects of errors for places with small populations:

$$PE_t = [(F_t - A_t)/A_t]\ (100)$$

In the above example, if the population of a county had been projected to be 55,000 in 2010 and the actual population turned out to be 50,000, the percent error would be (5,000/50,000) (100) = 10%. If the population had been projected to be 45,000, the percent error would be (−5,000/50,000) (100) = −10%.

Population counts from the decennial census are typically used as proxies for the "actual" population of an area. For postcensal or intercensal years, population estimates produced by the Census Bureau, state demographic agencies, or private data companies are often used. These proxies are not perfect, of course. Even census counts are subject to errors that may be substantial for a few places or demographic groups.

Enumeration and estimation errors undoubtedly have an impact on individual population forecast errors. They can either raise or lower errors, depending on whether they reinforce or offset the differences between projected and actual populations. Because of these offsetting effects—and the high levels of accuracy found in most census counts in the United States—the impact of enumeration/estimation errors on average forecast errors is probably not very great, especially for longer projection horizons. Most empirical studies do not attempt to adjust for enumeration or estimation errors when evaluating population forecast accuracy.

13.1.2 Common Error Measures

A number of summary error measures can be found in the general forecasting literature (Armstrong and Collopy 1992; Fildes 1992; Hyndman and Koehler 2006; Mahmoud 1987; Makridakis and Hibon 2000). We describe several, including the ones most commonly used to evaluate population forecasts.

The first two measures refer to the average error for a set of *n* individual forecasts:

$$\text{Mean Error (ME)} = \sum \mathrm{E_t}/\mathrm{n}$$
$$\text{Mean Absolute Error (MAE)} = \sum \left|\mathrm{E_t}\right|/\mathrm{n}$$

The first measure takes account of the direction of error; consequently, positive and negative errors offset each other. In fact, they could offset each other completely, resulting in a ME of zero even when individual errors are large. For example, three forecasts with errors of 400, 200, and −600 would yield a ME of zero.

The second measure ignores the direction of the errors, so positive and negative errors do not offset each other. This measure—sometimes called the *mean absolute deviation*—shows the average difference between forecasted and actual populations, regardless of whether the forecasts were too high or too low. Using the example cited above, forecasts with errors of 400, 200, and −600 would yield a MAE of 400.

These measures are based on the numerical differences between projected and actual populations; they do not account for differences in the size of the populations being projected. Yet a forecast error of 1,000 has a very different meaning for a place with 2,000 residents than a place with 200,000 residents. The next two measures account for population size by focusing on percent errors rather than numerical errors:

$$\text{Mean Algebraic Percent Error (MALPE)} = \sum \mathrm{PE_t}/\mathrm{n}$$
$$\text{Mean Absolute Percent Error (MAPE)} = \sum \left|\mathrm{PE_t}\right|/\mathrm{n}$$

The MALPE (often called the *mean percent error*) is a measure in which positive and negative values offset each other. Consequently, it is often used as a measure of bias (Chi 2009; Keilman 1999; Rayer 2008; Smith 1987; Tayman and Swanson 1996). A positive MALPE reflects a tendency for forecasts to be too high and a negative MALPE reflects a tendency for forecasts to be too low. The proportion of positive errors (%POS) or negative errors (%NEG) are other commonly used as measures of bias (Smith and Sincich 1992; Voss and Kale 1985; White 1954).

The MAPE, on the other hand, is a measure in which positive and negative values do not offset each other. It shows the average percent difference between forecasts and actual populations, regardless of whether the individual forecasts were too high or too low. The MAPE is a widely used measure of forecast accuracy, both in evaluations of population projections (Chi and Voss 2011; Long 1995; Rayer 2008; Smith 1987; Tayman and Swanson 1996) and in the general forecasting literature (e.g., Armstrong 1983; Ashton and Ashton 1985; Mahmoud 1984; Makridakis and Taleb 2009).

Sometimes it is important to use error measures that give more weight to large errors than small errors; for example, when a large error has a disproportionately large impact on the cost of being wrong. In these situations, the following measures can be used:

$$\text{Mean Squared Error (MSE)} = \sum (\text{E}_\text{t})^2/\text{n}$$

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\sum (E_t)^2/n}$$

Although these two measures are used for evaluating many types of forecasts (Armstrong and Collopy 1992; He and Xu 2005; Hendry and Clements 2004; Mahmoud 1987), they are of limited use for evaluating population forecasts because errors for places with large populations swamp errors for places with small populations. This problem can be dealt with by using percent errors rather than absolute errors. A number of studies have used the Root Mean Squared Percent Error (RMSPE) to evaluate population forecasts (Chi 2009; Chi and Voss 2011; Keilman 1990; Smith and Sincich 1992):

$$\text{Root Mean Squared Percent Error (RMSPE)} = \sqrt{\sum (PE_t)^2/n}$$

Some accuracy measures focus on other aspects of the distribution of errors rather than the mean value. The median absolute percent error (MEDAPE) is the percent error which falls right in the middle of the distribution: half the absolute percent errors are larger and half are smaller. This measure is useful when the objective is to highlight the "typical" error and ignore the effects of outliers. The 90th percentile error (90PE) is the absolute percent error larger than exactly 90% of all other absolute percent errors. This measure gives an indication of the range of errors and can be used to construct prediction intervals (Rayer et al. 2009; Smith and Sincich 1988; Tayman et al. 1998). We return to this topic later in this chapter.

Other error measures can also be used. Theil's U-statistic measures the difference between errors produced by a formal forecasting method and a naïve alternative, such as the assumption that no change will occur. This statistic squares the errors so that large errors are given heavier weights than small errors (Theil 1966). The proportionate reduction in error (PRE) also shows the extent to which a forecast can improve on the naïve assumption of no change, but without giving heavier weights to large errors (Tayman and Swanson 1996). In order to reduce the impact of outliers, some analysts have constructed mean errors based on statistical transformations of absolute percent errors (Mahmoud 1987; Tayman et al. 1999; Swanson et al. 2011).

All the measures discussed above focus on differences in population levels in the target year. This is the approach most commonly used to evaluate population forecast accuracy. An alternative approach focuses on differences between projected and actual *growth rates* rather than differences between projected and actual *population sizes*. Keyfitz (1981), Stoto (1983), Long (1995), and Mulder (2002) used this approach for evaluating national population projections; Tayman (1996) used it for evaluating census tract projections. This approach is often used for evaluating short-run economic and business forecasts, but is not commonly used for evaluating population projections. We present several examples of this approach later in this chapter.

13.1.3 Selection Criteria

In the general forecasting literature, accuracy measures are used not only to show how well forecasts have performed over the projection horizon, but also to show how well a particular model fit the data observed during the base period (Ascher 1981; Makridakis 1986; Pant and Starbuck 1990). For population projections, however, accuracy measures are generally used only to show how well (or poorly) projections have performed as forecasts of future population. Given the many different statistics that can be used to measure forecast accuracy and bias, how can one go about choosing the most appropriate measure(s)?

A number of researchers have discussed criteria that might be used to select measures of forecast error (Ahlburg 1995; Armstrong and Collopy 1992; Makridakis 1993; Rayer 2007; Swanson et al. 2011). Several criteria are mentioned frequently. Error measures should be reliable; that is, repeated applications should yield similar results. They should be valid, in the sense that they actually measure what they are purported to measure. They should convey as much information about forecast errors as possible and should be easy for the data user to understand. They should be sensitive to differences in error distributions, but should not be unduly influenced by outliers.

It has also been noted that error measures should be related to loss functions that specify the cost of forecast errors to data users (Ahlburg 1995; Fildes 1992). For example, if the cost of forecast errors is linear in absolute terms, an error measure such as the MAE is appropriate. If the cost of errors is linear in percent terms, a measure such as the MAPE is appropriate. If the cost of large errors is disproportionately high, a measure that assigns larger weights to larger errors is appropriate (e.g., MSE, RMSE, or RMSPE). If the direction of error is important, measures such as ME, MALPE, or %POS are useful. The best error measure for any given data user, then, depends on the purposes for which the projections are to be used.

However, data users rarely know the exact costs associated with forecast errors. Even if they did, loss functions would be difficult to estimate because error distributions are usually unknown and rarely conform to standard statistical assumptions (Armstrong and Fildes 1995; Bryan 1999). Perhaps more important, population projections are typically produced for general use rather than for a specific use by a particular data user. Consequently, it is impossible to specify a unique loss function that will be best for all data users and for all purposes. For these reasons, loss functions are seldom used to evaluate the forecast accuracy of population projections.

The MAPE is used more frequently than any other error measure in evaluations of population forecast accuracy (Ahlburg 1995; Swanson et al. 2011). It is a good choice as a general accuracy measure because it "incorporates the best characteristics among the various accuracy criteria" (Makridakis 1993, p. 528). Because of the impact of a few large errors, however, the MAPE may overstate the "typical" error in a set of projections; when this is a concern, the MAPE can be re-scaled (MAPE-R) to reduce the impact of outliers (Swanson et al. 2011; Tayman et al. 1999). Despite this shortcoming, we believe the MAPE provides a reasonable measure for evaluating forecast accuracy under a wide variety of circumstances.

The MALPE is widely used as a measure of bias and provides a simple but effective way to investigate the tendency for projections to be too high or too low. The next section discusses the empirical evidence on population forecast accuracy and bias, focusing on differences among methods and the effects of differences in population size, growth rate, length of base period, length of projection horizon, and launch year. Due to their generally favorable characteristics and frequency of use in the literature, the MAPE and MALPE are the measures we report most often.

Can valid conclusions be drawn when only a few error measures are analyzed? For most purposes, we believe they can. Although different error measures provide different perspectives on accuracy and bias, error patterns are generally stable across a variety of error measures (Rayer 2007). That is, the impact of factors such as population size, growth rate, and length of projection horizon on forecast accuracy is generally about the same regardless of which error measure is used. The same is true for alternative measures of bias. Consequently, we believe a few well-chosen error measures will be sufficient for most evaluation purposes.

When population projections are used to guide real-world decision making, however, the analyst should consider more than the standard measures of forecast error. In particular, it is important to consider the cost of being wrong. When population projections are used for planning the location of a retail outlet, constructing a new electric power plant, or adding a wing to a hospital, what are the implications of inaccurate forecasts? Will the cost of forecasting too little growth be considerably greater than the cost of forecasting too much growth? Will small errors have little impact on costs, but large errors have a disproportionately large impact? These are the types of questions the analyst must answer when using population projections to guide decision making.

13.2 Factors Affecting Accuracy and Bias

13.2.1 *Projection Method*

Projection methods differ tremendously in terms of data requirements, mathematical structure, degree of disaggregation, number of variables included, choice of assumptions, and modeling skills required. A common perception among both the producers and the users of population projections is that complex methods are more accurate than simple methods (Alho 1997; Beaumont and Isserman 1987; Irwin 1977; Keyfitz 1981; Pittenger 1980). Other analysts have challenged this perception, claiming it is not supported by the empirical evidence (Chi 2009; Kale et al. 1981; Pflaumer 1992; Rayer 2008; Smith and Sincich 1992). Who is right? Do increases in methodological complexity—including the use of structural and microsimulation models—lead to smaller forecast errors? More generally, what does the empirical evidence show regarding the accuracy of various population projection methods?

Before we can answer these questions, we must develop a framework for evaluating the complexity of various projection methods. Smith and Sincich (1992) classified methods according to their mathematical and causal structures. Mathematical structures range from very simple (e.g., linear extrapolation) to very complex (e.g., multi-regional cohort-component models). Causal structures may specify that population variables are affected solely by their own historical values (e.g., ARIMA time series models) or by other variables as well (e.g., structural models). Combining these two characteristics yields a 2-by-2 matrix with four types of methods: simple extrapolative, simple structural, complex extrapolative, and complex structural/microsimulation.

This classification scheme could be enriched by considering several additional factors. Long (1995) highlighted three types of complexity: model specification, degree of disaggregation, and the selection of assumptions and alternative scenarios. The complexity of a model is determined not only by its mathematical structure, but also by the number of factors it takes into account and the ease with which it can be explained to data users. The degree of disaggregation refers to the level of demographic detail provided by the projections (e.g., age, sex, race). Selection complexity is determined by the manner in which assumptions are made and by the number of alternative scenarios provided. In cohort-component models, for example, assumptions regarding future fertility, mortality, and migration rates may be based on their most recent values, on time series extrapolations of historical values, or on structural models. The number of scenarios may also vary widely. Projections from the Census Bureau have provided as many as 30 and as few as two alternative scenarios (Spencer 1989; Campbell 1996).

Other factors could be considered as well, such as linear vs. nonlinear models, the level of modeling skills required, and the degree of interaction among variables

(Armstrong 1985; Ascher 1981). It is unlikely that a standard classification scheme can be developed that will fully cover all the possibilities. Furthermore, as Rogers (1995) pointed out, the simple vs. complex classification is really a continuum rather than a dichotomy. Methods should be defined in relative rather than absolute terms, or as "simpler vs. more complex" rather than "simple vs. complex." Most methods can be classified as relatively simple when compared to one method and relatively complex when compared to another.

In this chapter we classify projection methods as relatively simple or complex according to their mathematical structures, data requirements, degree of disaggregation, and level of modeling skills required. We classify them as structural/microsimulation or extrapolative according to whether they are affected by economic and/or other variables or solely by their own historical values. Other things being equal, we view structural/microsimulation models as more complex than strictly extrapolative methods. According to these criteria, we rank commonly used projection methods as follows:

1. Simple: Linear extrapolation, exponential (or geometric) extrapolation, constant-share, shift-share, and share-of-growth methods. These methods are mathematically simple and require relatively little input data and few modeling skills.
2. More complex: Regression, logistic, and ARIMA time series models. These methods are considerably more mathematically complex and require more input data and modeling skills than simple trend extrapolation methods. However, they rely primarily on highly aggregated data and do not account for the effects of other variables.
3. Most complex: Cohort-component, structural, and microsimulation models. These models are mathematically complex, highly disaggregated, and require large amounts of input data. The assumptions used in these models can be relatively simple (e.g., fertility, mortality, and migration rates remain constant at current levels) or very complex (e.g., fertility, mortality, and migration rates are derived from structural or time series models).

The ranking of specific models and techniques is not always clear-cut. Cohort-component models have greater data requirements and a higher level of disaggregation than ARIMA time series models, but require fewer statistical modeling skills. Specific applications of the cohort-component method may themselves vary considerably in terms of simplicity or complexity. Structural and microsimulation models also vary a great deal, from simple recursive models containing few variables to large simultaneous equation models containing hundreds of variables and parameters. Box 13.1 lists abbreviations for the projection methods evaluated in this chapter.

Box 13.1 Abbreviations for Projection Methods

LINE: Linear extrapolation.

EXPO: Exponential extrapolation.

SHIFT: Shift-share.

SHARE: Share-of-growth (this method is sometimes called the apportionment method).

ARIMA: ARIMA time series model.

CB: Cohort-component model used by the Census Bureau.

NPA: Economic-demographic model used by the National Planning Association.

BEA: Economic-demographic model used by the Bureau of Economic Analysis (the BEA projections were formerly called OBERS, an acronym derived from the Office of Business Economics and the Economic Research Service).

13.2.1.1 Projections of Total Population

Numerous studies have evaluated the accuracy of forecasts of total population based on alternative projection methods. Although our list is no doubt incomplete, we summarize the results of all the studies we have seen. Of these studies, ten compared cohort-component models with one or more trend extrapolation methods; two compared structural models with cohort-component models that do not incorporate causal relationships; three compared structural models with trend extrapolation methods; and two compared a number of trend extrapolation methods, cohort-component models, and structural models. To our knowledge there have been no studies that have evaluated the accuracy of population forecasts from microsimulation models. What does the evidence show?

White (1954) compared the accuracy of cohort-survival projections for states with the accuracy of projections from a number of simple trend extrapolation methods: linear, geometric, and several ratio methods similar to SHIFT and SHARE. Using 1930–1940 and 1930–1950 as projection horizons, she found that errors from all the methods were about the same, except for one application of the SHIFT method, which had considerably larger errors than the other methods. Errors from the trend extrapolation methods were sometimes larger and sometimes smaller than errors from the cohort-survival model, but the differences were generally small, leading her to conclude that no particular method was clearly superior to all other methods.

Leach (1981) evaluated several sets of logistic, component, and cohort-component projections for the population of Great Britain. Using target years between 1931 and 1971, he found no evidence that component or cohort-component projections were consistently more accurate than logistic extrapolations. In fact, he concluded that the logistic curve can provide more reliable projections of total population than the component method. This study, however, was based on a fairly small number of empirical observations.

Kale et al. (1981) evaluated the forecast accuracy of several sets of population projections for states in the United States. This study covered early component projections, cohort-component projections produced by the Census Bureau, projections from a ratio technique, ARIMA time series models, and employment-based projections produced by the Bureau of Economic Analysis and the National Planning Association. These projections were made between the 1930s and the 1970s, with horizons ranging from 5 to 25 years. They found errors from all methods to fall within a fairly narrow range for any given length of projection horizon and concluded that the particular method used for population projections doesn't seem to matter.

Stoto (1983) compared 5- and 10-year cohort-component projections made by the United Nations in the 1950s and 1960s for 24 regions of the world with simple geometric extrapolations. He found the geometric extrapolations to exhibit almost no bias and to produce errors that were equal to or smaller than those produced by the cohort-component projections. He concluded that simpler methods were better than more complicated methods for some purposes.

Murdock et al. (1984) compared population projections from 1970 to 1980 for counties in North Dakota and Texas. Two sets of projections were made, one using a simple economic-demographic model and one using a traditional cohort-component model. They found the level of accuracy for these two sets of projections to be nearly identical.

Pflaumer (1992) compared the accuracy of ARIMA time series projections with the accuracy of traditional cohort-component projections of the U.S. population, using a variety of forecast horizons and launch years between 1930 and 1980. He found the errors to be similar and concluded that ARIMA models produce population forecasts that are at least as reliable as those produced by cohort-component models.

Using projection horizons ranging from 5 to 20 years, Long (1995) compared several sets of national and state-level cohort-component projections produced by the Census Bureau with those generated by simple geometric extrapolations. He found no consistent differences in forecast accuracy. In fact, for national projections the geometric extrapolations had smaller errors than the cohort-component projections in a large majority of the comparisons. He concluded that a case for complexity in projection methods cannot be made on the basis of accuracy alone. Mulder (2002) reported similar results in a study of 17 sets of national projections produced by the Census Bureau between the 1940s and 1990s; like Long, she found that the geometric extrapolations generally outperformed the cohort-component model.

Morgenroth (2002) evaluated the accuracy of 5-year projections based on cohort-component, regression-based, and simple extrapolation methods for counties in Ireland. He found the simple extrapolation methods to be at least as accurate—and in some instances considerably more accurate—than the more complex methods.

Wilson (2007) evaluated the accuracy of national population projections in Australia. He found the cohort-component projections produced in the 1960s and 1970s to be less accurate than the extrapolation of previous growth rates, but the opposite was true for projections produced in the 1980s and 1990s.

Rayer (2008) compared cohort-component projections for a sample of states, counties, and subcounty areas in the United States with averages based on several extrapolation methods. At every level of geography, he found accuracy and bias to be about the same for the trend extrapolations as for the cohort-component projections. He concluded that these two approaches to population projection generally provide similar results.

Chi (2009) developed several structural models incorporating a variety of demographic, socioeconomic, transportation, and land use characteristics for 1,837 minor civil divisions (MCDs) in Wisconsin. Using data from 1970 to 2000, he compared projections derived from the structural models with projections based on simple trend extrapolation methods. He found the former to be slightly more accurate but to display more bias. He concluded that the results did not support the premise that knowledge-based structural models can outperform simple extrapolation methods. Chi and Voss (2011) extended the analysis to include spatial effects that account for the spillover of population growth from one MCD to another but found errors for the structural models to be a bit larger than errors for the simple extrapolation methods. Chi et al. (2011) tested the model using data for census tracts in Milwaukee, again finding no improvement over the forecasting performance of simple extrapolation methods.

In perhaps the most comprehensive evaluation of subnational projections to date, Smith and Sincich (1992) evaluated five sets of state population projections with launch years ranging from the mid-1950s to the early 1980s and projection horizons extending from 5 to 20 years. Their analysis covered four simple trend extrapolation methods (LINE, EXPO, SHIFT, SHARE), an ARIMA time series model, the Census Bureau's application of the cohort-component method, and two employment-based structural models (one from the Bureau of Economic Analysis and the other from the National Planning Association). They used several measures of accuracy and bias, and conducted formal statistical tests of differences in errors by method. Table 13.1 summarizes the results, showing forecast errors averaged across all launch years. Errors for all series of Census Bureau projections have been averaged together and are depicted as CB.

Except for EXPO projections for longer forecast horizons (and, to a lesser extent, SHIFT projections), accuracy levels were similar for all projection methods. For 10-year horizons, for example, MAPEs for all projections fell between 6% and 7%. For 20-year horizons, the range was 11–16% (11–13%, excluding EXPO). The EXPO projections had a consistent upward bias and the ARIMA projections had a consistent downward bias; projections from the other methods displayed little tendency to be too high or too low. Analyses by method, launch year, and forecast horizon found differences in errors to be small and statistically insignificant for almost every possible combination of method, launch year, and horizon. The authors concluded that there is no evidence that complex and/or sophisticated techniques produce more accurate or less biased forecasts than simple, naive techniques.

Table 13.1 Measures of accuracy and bias for state population projections: averages covering all launch years

Measure	Technique	Length of projection horizon (Years)			
		5	10	15	20
MAPE	LINE	3.5	6.0	8.0	11.3
	EXPO	3.9	7.0	10.6	16.2
	ARIMA	3.3	6.3	9.1	11.5
	SHIFT	3.8	6.4	9.2	13.4
	SHARE	3.6	6.0	8.2	11.7
	CB	3.7	6.1	8.3	12.4
	NPA[a]	4.3	6.8	8.4	–
	BEA	4.0	6.5	9.1	12.8
RMSPE	LINE	5.1	8.2	10.8	14.3
	EXPO	6.3	11.7	20.2	33.0
	ARIMA	4.6	8.2	11.7	14.8
	SHIFT	5.5	9.3	13.2	18.7
	SHARE	5.2	8.4	11.3	15.2
	CB	5.0	8.2	10.7	15.1
	NPA[a]	5.3	8.5	10.3	–
	BEA	5.8	8.8	11.6	15.2
90PE	LINE	7.7	11.8	26.4	22.3
	EXPO	8.6	13.6	21.3	32.0
	ARIMA	7.2	13.6	18.9	23.6
	SHIFT	8.1	13.1	19.5	27.7
	SHARE	7.8	12.1	17.9	23.4
	CB	8.1	13.2	17.5	24.7
	NPA[a]	8.3	13.4	17.9	–
	BEA	9.7	14.1	18.3	26.1
MALPE	LINE	0.1	−0.5	−1.1	−1.9
	EXPO	1.2	2.4	4.3	7.8
	ARIMA	−1.1	−2.8	−4.4	−6.0
	SHIFT	0.4	0.2	−0.2	−0.8
	SHARE	0.4	0.2	0.2	0.4
	CB	−0.7	−1.1	−0.4	2.4
	NPA[a]	−2.4	−0.9	−0.6	–
	BEA	1.7	−3.6	−2.6	−4.9
% POS	LINE	51.3	46.7	47.5	44.7
	EXPO	59.0	60.4	61.5	60.7
	ARIMA	40.6	40.0	36.0	34.7
	SHIFT	54.0	51.6	51.5	46.7
	SHARE	54.0	51.2	54.0	49.3
	CB	44.4	46.0	50.3	55.7
	NPA[a]	33.0	46.0	49.0	–
	BEA	64.0	34.0	43.0	40.0

Source: Smith and Sincich (1992)

[a]20-year projection horizon not available

We know of only two empirical studies that have not shared this conclusion. Keyfitz (1981) compared national cohort-component projections published by the United Nations in the late 1950s with projections based on the extrapolation of 1950–1955 exponential growth rates. He found the cohort-component projections to have smaller forecast errors than the exponential extrapolations. When he used projected growth rates for 1955–1960 instead of actual growth rates for 1950–1955 as the base for the exponential extrapolations, however, much of the difference in errors was wiped out. It also should be noted that for long-range projections, 5-year base periods (such as those used by Keyfitz) have been found to produce larger forecast errors than either 10- or 20-year base periods, especially for the exponential method and for rapidly growing areas (Smith and Sincich 1990). We return to this issue later in this chapter.

Sanderson (1999) evaluated projections of the world population and projections of birth and death rates for several countries. He compared results from standard cohort-component models with results from structural models. He found that projections from the structural models were more accurate than cohort-component projections in the majority of the comparisons. Recognizing the limitations of his very small sample size, however, Sanderson stopped short of concluding that structural models *generally* provide more accurate forecasts than extrapolation methods. Rather, he concluded that structural models can improve forecast accuracy when projections from structural models are averaged together with projections from other models. We return to the potential benefits of combining forecasts later in this chapter. It also should be noted that Sanderson's study covered birth and death rates but did not consider migration, the most volatile component of population growth at the state and local level.

The Census Bureau sponsored a great deal of research on the development of economic-demographic projection models during the 1980s (Long and McMillen 1987). The resulting model for states—called ECESIS—was found to be more useful for simulation purposes than for population forecasting and the Census Bureau has never used the model for its "preferred" series of state projections; instead, it continued to use trend extrapolation methods for projecting components of growth (Campbell 1994, 1996; U.S. Census Bureau 2005). Although a structural model was used in the mid-1990s to produce an alternative series of migration projections, extrapolation methods were considered to be the best available for state projections (Campbell 1996).

There is a substantial body of evidence, then, supporting the notion that more complex methods—including structural models—do not produce more accurate forecasts of total population than can be achieved with simple trend extrapolation methods; in fact, some studies have found the opposite to be true. There is very little evidence suggesting that more complex methods consistently produce more accurate forecasts than simple methods. We believe the weight of the evidence is sufficient to conclude that—to date—neither the sophistication of structural models nor the complexity of time series and cohort-component models has led to consistently greater forecast accuracy for projections of total population than can be achieved with simple extrapolation methods.

Why is it that complex methods do not produce more accurate forecasts than simpler methods? We believe there is a certain irreducible level of uncertainty regarding the future. No projection method—no matter how complex or sophisticated—can consistently improve forecast accuracy beyond that level. Based on the evidence to date, it appears that the relatively small amount of historical information contained in simple trend and ratio extrapolation methods provides as much guidance to this uncertain future as does the much larger amount of information contained in more complex and sophisticated methods.

Cohort-component projections are generally no more accurate than trend extrapolations because forecasting fertility, mortality, and migration rates is just as difficult as forecasting changes in total population (perhaps more difficult). This difficulty offsets the potential advantages offered by data disaggregation and the stability of the age-sex structure. Will the application of time series methods or the development of new data sources improve the accuracy of cohort-component projections? We doubt it. Projections will still be based on the extrapolation of past trends, and those trends will most likely be highly correlated with those underlying the simple extrapolation methods. It is unlikely that more complex approaches to extrapolating past trends will lead to any significant improvements in forecast accuracy.

What about structural and microsimulation models? Might improvements in those models lead to improvements in forecast accuracy? Again, we are doubtful. Knowledge regarding the determinants of population change is far from perfect. Consequently, it is impossible to construct models that realistically incorporate the effects of all the factors affecting population change. Even if such models could be constructed, there is no certainty that past relationships between independent and dependent variables will remain constant in the future. More critical yet, even if those relationships were to remain constant, the future values for the independent variables themselves would still be unknown. Is there is any reason to believe these variables can be projected more accurately than demographic variables? We do not believe so. In fact, given the relative stability of demographic processes, the opposite is more likely true.

We do not mean to imply that all relatively simple methods perform equally well under all circumstances. On the contrary, there are circumstances in which some simple methods produce less accurate or more biased forecasts than other simple methods or more complex methods. We investigate some of these possibilities later in this chapter. "Simple" should not be confused with "simplistic." Informed judgment is needed to determine when and how simple methods can best be applied.

One further caveat should be mentioned. Most of the empirical studies discussed above focused on projection horizons ranging between 5 and 25 years. Little empirical evidence exists for very short horizons (i.e., less than 5 years) or very long horizons (i.e., greater than 25 years). Our conclusions regarding forecast accuracy thus refer to projections spanning horizons of 5–25 years. We will look at the relationship between forecast errors and length of forecast horizon later in this chapter.

13.2.1.2 Projections in Other Fields

The discussion so far has focused exclusively on the forecast accuracy of population projections. What about studies of forecast accuracy in other fields, such as business, economics, political science, sociology, psychology, and meteorology? What does the evidence show regarding the forecasting performance of different methods? In particular, how do simple methods compare with more complex methods and how do structural models compare with strictly extrapolative methods?

Studies covering variables as diverse as GNP, employment, inflation, housing starts, company earnings, sales of particular products, market share, crime rates, psychiatric diagnoses, and annual rainfall have found results similar to those reported here for population projections. Many analysts have concluded that complex or statistically sophisticated forecasting methods are generally no more accurate than simpler methods (Armstrong 1985; Ascher 1981; Crone et al. 2011; Mahmoud 1984; Makridakis and Hibon 2000; Schnaars 1986). Others have concluded that structural models are generally no more accurate than trend extrapolation methods (Brodie and De Kluyver 1987; LeSage 1990; Makridakis 1986). Some have even questioned the value of incorporating expert judgment in the forecasting process, at least beyond some minimal level (Pant and Starbuck 1990).

There is not unanimity on these conclusions, however, particularly with respect to the benefits of structural models. A number of analysts believe that structural models *do* produce more accurate forecasts than strictly extrapolative methods, at least for short projection horizons (Armstrong 1985; Batchelor and Dua 1990; Clemen and Guerard 1989; Fildes 1985; Leitch and Tanner 1995). For example, West and Fullerton (1996) made forecasts of a number of economic and demographic variables for metropolitan areas in Florida, using structural models and four different trend extrapolation methods. Their forecasts extended from one to ten quarters. They found that on average the structural models performed better than the extrapolation methods. However, the relative performance of several of the extrapolation methods improved as the forecast horizon increased, so that by the ninth and tenth quarters errors for the extrapolation methods were virtually identical to those for the structural models. They also found that differences in the complexity of extrapolation methods had no impact on forecasting performance: simple linear and exponential extrapolations performed just as well as more complex time series models.

Most of the studies from non-demographic fields focused on forecasts of 2 years or less. This time frame is very different from that used in most studies of population projections, which typically focus on horizons of 5 years or longer. Consequently, it is important to note that several of the studies finding that structural models produce more accurate forecasts than trend extrapolation methods also found the superiority of structural models to decline as the forecast horizon increased. Clemen and Guerard (1989) and Leitch and Tanner (1995) found the superior performance of structural models to disappear within four quarters; West and Fullerton (1996) found the same result within ten quarters. Armstrong (1985), however, reported exactly the opposite: Structural models are likely to be more accurate than strictly extrapolative models for long-term forecasts, but not for short-term forecasts.

13.2.1.3 Evaluating the Evidence

A substantial body of evidence supports the conclusion that more complex methods generally do not lead to more accurate forecasts of total population than can be achieved with simpler methods. This evidence has been drawn from studies covering a wide variety of methods, launch years, forecast horizons, and geographic regions. Studies from other fields have found similar results. Although one method may have greater accuracy than another for a particular set of projections, no single model or technique is *consistently* more accurate than all the others. On the contrary, most models and techniques produce similar results when applied in similar circumstances (e.g., launch year, target year, level of geography).

This does not imply, of course, that complex methods should never be used. There are many purposes for which complex methods are very useful, such as evaluating components of growth, providing demographic detail, conducting simulations, evaluating alternative scenarios, and connecting population projections to other types of projections. The political benefits of complex methods may also be important in some circumstances. Complex methods (including structural and microsimulation models) clearly have several important advantages over simple extrapolation methods. Greater forecast accuracy, however, is not one of them.

13.2.2 Population Size

Many studies covering a variety of projection methods, geographic regions, launch years, and time horizons have found forecast accuracy to improve as population size increases (Isserman 1977; Murdock et al. 1984; Rayer 2008; Smith and Sincich 1988; White 1954). This relationship has been found even when the effects of variables such as the population growth rate have been accounted for (Rayer and Smith 2010; Smith 1987; Tayman et al. 2011). Similar results have been found in evaluations of population estimates.

A number of studies, however, have found this relationship to weaken (or disappear completely) once a certain population size has been reached (Schmitt and Crosetti 1951; Smith 1987; Smith and Shahidullah 1995; Tayman 1996; Tayman et al. 2011). The threshold level at which the relationship begins to weaken varies with the size of the geographic unit under consideration. For example, the relationship begins to weaken at a smaller population size for projections of counties than for projections of states. It appears that not only does population

Table 13.2 Errors for 1980 county population projections by size

		MAPE			
Population size in 1970	N	LINE	EXPO	SHIFT	Average
<5,000	302	20.8	18.0	25.1	21.2
5,000–14,999	918	15.9	14.7	18.4	16.3
15,000–24,999	555	12.6	11.8	14.4	12.9
25,000–49,999	539	11.8	11.3	13.0	11.9
50,000–99,999	324	10.2	11.0	11.3	10.7
100,00+	333	9.3	11.7	10.5	10.3
All counties	2,971	13.7	13.1	15.7	14.1
		MALPE			
Population size in 1970	N	LINE	EXPO	SHIFT	Average
<5,000	302	−18.0	−14.2	−22.3	−18.2
5,000–14,999	918	−15.0	−13.5	−17.7	−15.4
15,000–24,999	555	−11.7	−10.5	13.5	−11.9
25,000–49,999	539	−9.1	−7.2	−10.0	−8.8
50,000–99,999	324	−5.6	−1.9	−5.7	−4.4
100,00+	333	2.7	7.4	3.3	4.5
All counties	2,971	−10.6	−8.3	−12.3	−10.4

Source: Smith (1987)

size matter, but so does the relationship between population size and the size of the geographic area.

A clear relationship between forecast errors and population size is generally found only for measures of accuracy (e.g., MAPE), not for measures of bias (e.g., MALPE). A number of studies have found no consistent relationship between population size and bias (Murdock et al. 1984; Rayer and Smith 2010; Smith and Sincich 1988). Even when a relationship is found, it is often specific to a particular projection method or time period or is caused by a spurious correlation rather than by population size per se (Smith 1987; Tayman et al. 1998). Although the evidence is not completely clear-cut, it appears that population size has no predictable impact on the tendency for population projections to be too high or too low.

Table 13.2 illustrates the relationship between population size and forecast errors. It shows errors for 10-year projections for counties in the United States (Smith 1987). For all four projection methods, MAPEs declined steadily as population size increased. MAPEs for the smallest counties were approximately twice as large as MAPEs for the largest counties. Differences in MAPEs among the smallest size categories were quite large, but differences among the largest categories were very small. MALPEs also showed a strong positive relationship with population size, but this relationship was spurious, caused by a positive correlation between population size and growth rate.

The effect of population size on forecast accuracy can also be seen by comparing errors for different types of geographic units. For 10-year projection horizons, MAPEs for states generally average 4–8% (Kale et al. 1981; Smith and Sincich 1988, 1992; White 1954). For counties, they generally average 8–14% (Murdock et al. 1984; Rayer 2008; Smith 1987). For census tracts and similarly sized areas, they generally average 15–21% (Murdock et al. 1984; Rayer and Smith 2010; Smith and Shahidullah 1995; Tayman 1996). For areas smaller than census tracts, errors are even larger (Tayman et al. 1998, 1999). Clearly, the larger the population of the area to be projected, the more accurate the forecast is likely to be.

13.2.3 Population Growth Rate

Population growth rates also have a strong impact on forecast errors. Growth rates can be measured for either the base period or the projection horizon. Both approaches are valid for analytical purposes, but we believe it is more useful to focus on the base period because information on growth rates over the projection horizon is not available at the time a set of projections is made. Consequently, if insights gained from studying the relationship between growth rates and forecast accuracy are to be used in making population projections, they must be based on growth rates during the base period.

MAPEs have been found to be smallest for places with small but positive growth rates over the base period and to increase as growth rates deviate in either direction from those low levels (Rayer 2008; Rayer and Smith 2010; Smith 1987; Smith and Shahidullah 1995; Tayman et al. 2011). That is, there is a U-shaped relationship between forecast accuracy and population growth rates, with the largest errors typically found for places that are either growing or declining rapidly.

Bias is also strongly affected by differences in population growth rates. A number of studies have found that places losing population over the base period tend to be under-projected whereas rapidly growing places tend to be over-projected (Rayer 2008; Rayer and Smith 2010; Smith 1987; Smith and Shahidullah 1995; Tayman et al. 2011).

Table 13.3 uses the same county projections as Table 13.2. For all four methods, there is a strong U-shaped relationship between growth rates and MAPEs. MAPEs were smallest for counties with growth rates between 0% and 15%, somewhat larger for counties with growth rates of 25–50% or with moderate negative growth rates, and much larger for counties with growth rates above 50% or below -10%. The effect of very high growth rates on errors was greatest for EXPO and the effect of very low growth rates was greatest for SHIFT.

Table 13.3 also shows a strong positive relationship between growth rates and MALPEs. MALPEs have large negative values for counties losing more than 10% of their populations during the base period, but those values increase steadily as the growth rate increases, eventually reaching positive levels for three of the four projection methods. The SHIFT method had the strongest downward bias for counties losing population and the EXPO method had the strongest upward bias for rapidly growing counties.

What caused the patterns shown in Table 13.3? We believe they were caused by the tendency for extreme growth rates to regress toward the mean over time (Smith 1987).

Table 13.3 Errors for 1980 county population projections by growth rate

MAPE					
Population growth rate 1960–1970	N	LINE	EXPO	SHIFT	Average
<−10%	516	20.5	17.0	25.0	20.8
−10–0%	800	13.3	13.0	15.8	14.0
0–10%	766	10.6	10.5	12.0	10.9
10–25%	558	11.0	10.8	11.9	11.2
25–50%	243	13.9	13.9	14.5	13.9
50–100%	75	19.8	23.7	20.3	20.3
100%+	13	24.1	47.5	24.6	28.3
All counties	2,971	13.7	13.1	15.7	14.1
MALPE					
Population growth rate 1960–1970	N	LINE	EXPO	SHIFT	Average
<−10%	516	−20.3	−16.6	−24.9	−20.6
−10–0%	800	−12.5	−12.2	−15.2	−13.3
0–10%	766	−8.2	−8.0	−9.8	−8.7
10–25%	558	−4.9	−3.0	−5.3	−4.4
25–50%	243	−6.1	0.6	−4.6	−3.4
50–100%	75	−6.0	12.1	−1.3	1.6
100%+	13	−6.1	40.4	1.4	11.9
All counties	2,971	−10.6	−8.3	−12.3	−10.4

Source: Smith (1987)

As shown in Table 13.4, the vast majority of counties that lost population or grew very slowly during one decade grew more rapidly during the following decade (or lost less rapidly). Conversely, the vast majority of counties that grew very rapidly during one decade grew more slowly during the following decade. As a consequence, projections based on periods of very rapid growth are likely to be too high and projections based on periods of large population declines are likely to be too low. This "regression toward the mean" phenomenon provides an explanation not only for the U-shaped relationship between growth rates and MAPEs, but also for the strong positive relationship between growth rates and MALPEs.

Why do growth rates regress toward the mean over time? To answer this question, we must consider the components of growth. Migration is typically the demographic variable most responsible for differences in growth rates among states and local areas (Congdon 1992; Cushing and Poot 2004; Smith and Ahmed 1990). Mortality and fertility rates do not differ nearly as much from place to place as do migration rates, and do not change as rapidly over time. For states and local areas, then, migration is the demographic variable that usually contributes most to differences in population growth rates and to changes in those rates over time.

In order for rapidly growing areas to maintain high growth rates, levels of net in-migration must continue increasing year after year. Yet if out-migration rates are based on the size of an area's population and in-migration rates are based on the size of the population outside that area, levels of net in-migration can increase only if in-migration rates go up or out-migration rates go down (Smith 1986). Similarly,

Table 13.4 Comparison of decade growth rates for counties, 1950–1980

Growth rate in decade t	N	Counties with higher growth rate in decade t + 1 than decade t	
		Number	Percent
<−10%	1,271	1,125	88.5%
−10–0%	1,532	1,221	79.7%
0–10%	1,354	883	65.2%
10–25%	1,031	487	47.2%
25–50%	485	157	32.4%
50–100%	213	42	19.7%
100%+	56	3	5.4%
All counties	5,942	3,918	65.9%

Source: Smith (1987)

for areas losing population, levels of net out-migration must eventually decline because the source of out-migrants is growing more slowly than the source of in-migrants. As a result, it is unlikely that an area will maintain an extremely high or low rate of population growth for extended periods of time.

There are several other reasons for expecting extreme migration rates to become more moderate over time. Rapidly growing areas have increasing numbers of "migration-prone" residents who are likely to move again, whereas declining areas have declining numbers of such residents. Some in-migrants may become disenchanted with their new locations and return to their former places of residence. It could also be argued that migration itself is a "self-equilibrating mechanism" that causes the comparative advantage of one area over another to fade over time, leading to more moderate rates of in- or out-migration (Greenwood 1997; Hunt 1993; Sjaastad 1962).

In summary, theory and empirical evidence both suggest that extreme growth rates are likely to regress toward the mean over time. Consequently, projections based on historical growth trends will often be too high for rapidly growing areas and too low for declining or very slowly growing areas. As we explain later in this chapter, this finding provides a basis for developing an alternative approach to the construction of population projections.

13.2.4 Length of Horizon

On average, forecast accuracy declines as the projection horizon becomes longer. This result has been found in many studies of population projections (Keilman 1990; Keyfitz 1981; Rayer 2008; Smith and Sincich 1992) as well as studies in other fields (Batchelor and Dua 1990; Makridakis and Hibon 2000; Schnaars 1986; Zarnowitz 1984). Such a result is not surprising, of course. The farther into the future a projection extends, the greater the opportunity for unforeseen events to occur and for factors affecting population growth to diverge from their predicted trends.

What does the error-horizon relationship look like? Several studies in the general forecasting literature have reported errors that grew about linearly with increases in the projection horizon (Ascher 1981; Schnaars 1986). Many studies of population projections have found the same thing for measures of accuracy (Kale et al. 1981; Rayer 2008; Rayer and Smith 2010; Schmitt and Crosetti 1951; Smith 1987; White 1954). Table 13.1 illustrates this relationship for several projection methods and measures of error.

Smith and Sincich (1991) analyzed the error-horizon relationship in detail, testing for linearity using several projection methods, measures of error, launch years, size categories, and growth-rate categories. They made projections for states using four simple extrapolation methods (LINE, EXPO, SHIFT, SHARE), 10-year base periods, and launch years at the beginning of every decade between 1910 and 1970. Projection horizons ranged from 5 to 50 years, in 5-year intervals.

For all four methods, they found MAPEs to increase about linearly as the projection horizon increased to 35 years; after 35 years, MAPEs began to deviate from the linear trend (especially for the EXPO technique). The same basic results were found for projections for each individual launch year and when states were divided into size and growth-rate categories. Statistical tests provided formal confirmation of this generally linear relationship. The only exceptions were MAPEs produced by the EXPO projections, which grew at an increasing rate for states with high growth rates during the base period. An approximately linear relationship was found for several other measures of forecast accuracy as well (e.g., RMSPE, 90PE), but it was not as strong as the relationship for MAPE. The MAPE-horizon relationship is illustrated in Fig. 13.1 for the LINE and EXPO methods.

Keyfitz (1981) and Stoto (1983) analyzed a large number of population projections made for countries using the cohort-component method and several extrapolation methods. Instead of using the MAPE as a measure of error, they focused on the difference between the projected rate of population increase and the actual rate realized over time. They concluded that this difference tends to remain constant over the entire length of the projection horizon.

This conclusion is virtually the same as Smith and Sincich's conclusion that the MAPE grows about linearly with the projection horizon. For example, if the projected rate of increase differed from the actual rate by 1% per year, differences between the projected and actual populations would be about 5% after 5 years, about 10% after 10 years, and so forth. The only differences would be caused by the effects of compounded growth rates, which would be small for short-and medium-range projections.

Further research will add to our ability to generalize these results. Would a linear relationship be found for other measures of error? Would it be found for other commonly used projection methods? Would similar results be found for small geographic units, which often exhibit high levels of growth-rate volatility over time? Would a linear relationship be found for projections of fewer than 5 years? What about horizons of 40 or 50 years? There are still many gaps in our

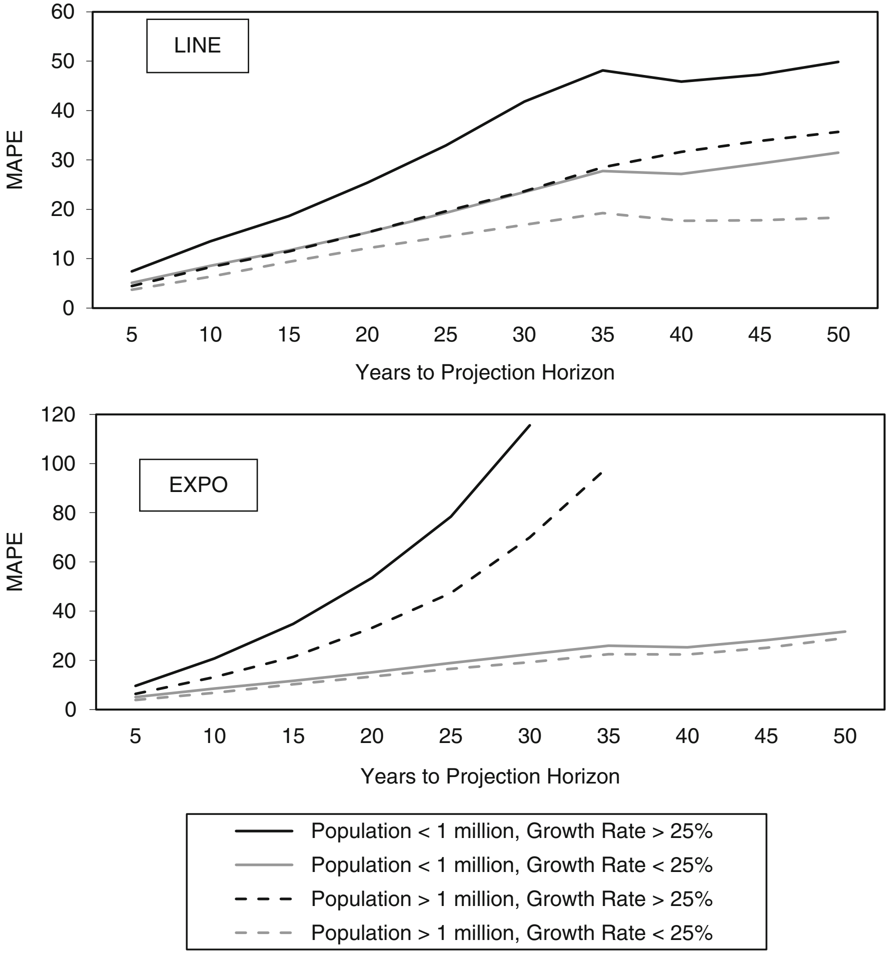

Fig. 13.1 MAPEs for state population forecasts by length of horizon (Source: Smith and Sincich 1991)

understanding of the relationship between population forecast errors and the length of the projection horizon.

The empirical regularities discussed above refer only to measures of accuracy, not to measures of bias. Most studies have focused solely on accuracy, but those that also considered bias reported no clear consistent relationship between forecast errors and the length of the projection horizon. Smith and Sincich (1991) found MALPEs to differ from one projection method to another, from one size-growth category to another, from one launch year to another, and over the length of the projection horizon. Table 13.1 shows no clear relationship between measures of bias (MALPE and %POS) and the length of the projection horizon. We do not believe the length of the projection horizon has any consistent impact on the tendency for projections to be too high or too low.

13.2.5 Length of Base Period

The length of the base period is one of the most fundamental decisions that must be made when producing population projections, but few studies have considered how this decision is made and what effect it has on population forecast errors. If simple extrapolation methods are used, what historical period should be used as the basis for those extrapolations? If a time series model is used, how many observations are needed? If a cohort-component model is used, what historical time period should be considered in choosing the appropriate mortality, fertility, and migration rates? How many data points are needed to construct reliable structural models?

A common rule of thumb for trend extrapolation methods is that the length of the base period should roughly correspond to the length of the projection horizon (Alho and Spencer 1997; Kale et al. 1985). For example, 5 years of base data may be sufficient for a 5-year projection, but 20 years of data are needed for a 20-year projection. Is this valid? What does the empirical evidence show?

Smith and Sincich (1990) made population projections for states using three simple extrapolation methods (LINE, EXPO, SHIFT) and annual population data from 1900 to 1980. Projections were made for 1-, 5-, 10-, 20-, and 30-year horizons using base periods of 1, 5, 10, 20, 30, and 40 years. For all three methods they found that MAPEs for 1-year horizons were virtually identical for base periods of 1, 5, 10, and 20 years; they were slightly larger for base periods of 30 and 40 years. For 5-year horizons there was a barely discernible U-shaped relationship between MAPEs and the length of the base period. For all three methods, projections derived from 10-year base periods had slightly smaller MAPEs than projections derived from either shorter or longer base periods. They concluded that for short projection horizons, differences in the length of the base period have very little impact on forecast accuracy.

For longer horizons, however, differences in the length of the base period had a much larger impact (Fig. 13.2). For LINE and SHIFT, MAPEs declined steadily as base periods increased from 1 to 5 to 10 years, but changed very little thereafter. This pattern was found for all three horizons, but was most consistent for 20- and 30- year horizons. For EXPO, a similar pattern was found for the 10-year horizon, but for the 20- and 30-year horizons MAPEs continued to decline as the base period increased to 40 years. For increases in base periods beyond 20 years, however, the declines were very small.

The authors refined their analysis by controlling for the effects of population size and growth rate (not shown here). They concluded that except for EXPO and SHIFT projections of rapidly growing states, increasing the base period beyond 10 years did not lead to greater forecast accuracy. In fact, longer base periods sometimes led to larger forecast errors. It appears that too short a base period

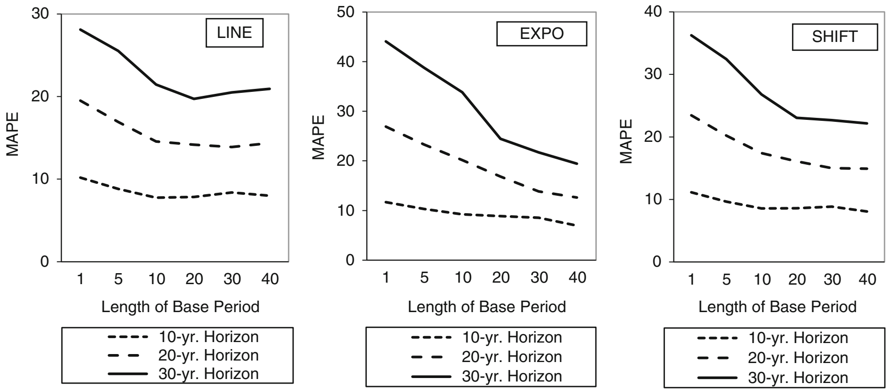

Fig. 13.2 MAPEs for state population forecasts by length of base period and length of horizon (Source: Smith and Sincich 1990)

(e.g., 1 or 5 years) may incorrectly interpret short-run fluctuations as long-run trends, whereas too long a base period (e.g., 30 or 40 years) may reflect historical trends that are no longer valid. For EXPO and SHIFT projections of rapidly growing states, however, increasing the base period from 10 to 20 years led to substantial improvements in forecast accuracy, especially for the 30-year horizons. Increases beyond 20 years generally led to no further improvements.

Why does a longer base period improve the forecasting performance of the EXPO and SHIFT methods in rapidly growing places? Again, we believe the explanation lies with the tendency for extreme growth rates to regress toward the mean over time (Smith 1987). For rapidly growing places, the EXPO method projects a high, unchanging growth rate and the SHIFT method projects an increasing share of the parent population. Very high growth rates, however, are generally not maintained for long periods. Consequently, using a longer base period helps reduce the large errors and strong upward bias often found in EXPO and SHIFT projections for places that grew rapidly during the 10 years immediately before the launch year.

Smith and Sincich (1990) also considered whether differences in the length of the base period have an impact on the tendency of population projections to be too low or too high. They found no consistent relationship between MALPEs and the length of the base period. They concluded that the degree of bias for simple extrapolation methods was not significantly affected by differences in the length of the base period.

How do the results reported by Smith and Sincich compare with those found in other studies of population projections? Using a ratio method similar to SHIFT, White (1954) found that a 60-year base period led to considerably larger errors in projections of state population than did a 30-year base period. Voss and Kale (1985) made forecasts of minor civil divisions in Wisconsin and found that a 30-year base period produced slightly more accurate forecasts than a 10-year base period for the EXPO technique. They also found that weighting more recent decades in the base period more heavily than more distant decades improved forecast accuracy. Beaumont and Isserman (1987) made LINE and EXPO projections for states that grew by more than 20% during the decade immediately prior to the launch year. For EXPO projections they found that a 40-year base period produced smaller errors and less upward bias than a 10-year base period; for LINE, however, they found that a 40-year base period did not improve forecast accuracy and led to considerably more bias. Rayer (2008) evaluated 10-, 20- and 30-year base periods for county projections based on several extrapolation methods and lengths of horizon. He found only slight differences in most instances. The only exception was for EXPO projections covering a 30-year horizon, for which a 20-year base period yielded a substantially smaller error than a 10-year base period. The results of all these studies were generally consistent with those reported by Smith and Sincich (1990).

At the beginning of this section we cited a rule of thumb stating that—for extrapolation methods—the length of the base period should roughly correspond to the length of the projection horizon. The evidence we have presented supports that rule to some extent, but not completely. For short-range projections, a short period of historical data appears to be sufficient. For long-range projections, at least 10 years of base data are needed to achieve the best possible results. However, base periods longer than 10 years are generally not necessary, and may even cause forecast accuracy to deteriorate. The only exceptions are EXPO and SHIFT projections of rapidly growing areas (and, to a smaller degree, SHIFT projections of declining areas), where increasing the base period to 20 years seems to improve forecast accuracy by moderating the impact of extreme growth rates.

The studies cited above used simple extrapolation methods for projecting total population. Little research on this issue has been done for other projection methods. In a study of cohort-component projections for the Netherlands, Keilman (1990) found that 10 years of base data led to more accurate forecasts of deaths than did 5 years of base data; however, he found no significant impact of differences in base period on forecasts of births. We are not aware of any other studies on this topic.

There is no uniformity among practitioners regarding the choice of the base period to be used for population projections. Simple extrapolation methods have been applied using anywhere between 1 and 60 years of base data. Time series models often use 50 or more observations, but some demographic applications have used as few as 11 (Voss and Kale 1985). Some cohort-component models use only the most recent data for constructing mortality, fertility, and migration rates, while others use a long time series or rely on expert judgment. For structural models the length of base period seems to depend primarily on the number of years for which relevant data series are available. Although the evidence is clear for simple extrapolation methods, more research is needed before we can draw firm conclusions regarding the optimal length of base period for other projection methods.

13.2.6 Launch Year

Some time periods are characterized by a high degree of stability in demographic trends while others are characterized by sudden dramatic changes. Since all objective projection methods are extrapolations of one type or another, the degree of stability is likely to have an impact on forecast accuracy. It might therefore be expected that forecast errors would be larger for some time periods (i.e., launch years) than for others. In fact, a number of researchers have found this to be true, at least to some extent (Long 1995; Mulder 2002; Rayer et al. 2009; Smith and Sincich 1988).

Long (1995) evaluated forecast errors for a number of national and state projections produced by the Census Bureau. At the national level he evaluated projections made between the mid-1940s and mid-1980s, using the RMSE of the annual growth rate as a measure of error. For 5-year horizons, he found the RMSE to vary from less than 0.1% to almost 1.0%. For 15-year horizons, it varied from less than 0.2–1.1%. Errors were highest for projections made during the mid-1940s, but showed no clear trend from the 1950s onward, bouncing up and down from one launch year to another. Mulder (2002) also reported substantial differences from one launch year to another in a study of the Census Bureau's national projections.

For state projections, Long evaluated projections made between the mid-1960s and mid-1980s. For 5-year horizons, he found MAPEs to vary between approximately 3% and 5%. For 15-year horizons, MAPEs varied from less than 6% to more than 12%. Again, there was no clear trend regarding changes in accuracy over time.

The proportional differences in accuracy by launch year noted by Long were considerably smaller for state projections than for national projections. This is because errors for state projections were based on averages covering all states, whereas errors for national projections were based on a single projection for each launch year. Generally, one would expect more instability in error characteristics for a single place than for an average covering many places.

Smith and Sincich (1988) also evaluated the forecast accuracy of state projections, but covered a broader range of launch years, considered the direction of errors as well as their magnitude, and evaluated variances as well as means. Using 10-year base periods and 10- and 20-year horizons, they made projections for the 50 states using four trend extrapolation methods (LINE, EXPO, SHIFT, SHARE) and an average of the projections from all four methods (AVE). They used all decennial census years from 1910 to 1980 as launch years. Table 13.5 shows the MAPEs and MALPEs for the 10-year projections, by launch year.

MAPEs were largest for the 1910 launch year, especially for the EXPO method. Thereafter, MAPEs fluctuated within a range of approximately 4–8%, with most falling between 6% and 8%. After 1910, there was no apparent trend over time: MAPEs sometimes increased from one launch year to the next and sometimes

Table 13.5 Errors for 10-year population projections for states by launch year, 1910–1980

MAPE					
Launch year	LINE	EXPO	SHIFT	SHARE	Average
1910	8.4	15.6	9.5	11.0	10.9
1920	6.6	7.3	6.7	7.4	7.0
1930	6.5	8.6	7.1	7.8	7.5
1940	7.9	7.3	7.8	7.8	7.7
1950	6.9	5.6	6.6	6.7	6.4
1960	4.4	7.3	5.0	6.0	5.6
1970	8.4	7.9	8.3	8.5	8.2
1980	6.1	8.0	6.9	6.4	6.2
MALPE					
Launch year	LINE	EXPO	SHIFT	SHARE	Average
1910	5.2	14.1	7.1	7.9	8.6
1920	−1.4	1.2	−0.6	−0.8	−0.4
1930	3.5	5.9	4.4	3.8	4.4
1940	−6.8	−5.9	−6.6	−6.6	−6.5
1950	−5.2	−2.6	−4.5	−4.7	−4.2
1960	1.3	5.4	2.4	2.0	2.8
1970	−3.7	−1.7	−3.1	−3.3	−2.9
1980	3.5	6.4	4.5	4.2	3.6

Source: Smith and Sincich 1988, 1992 and unpublished data

declined. These data show some variation from one launch year to another, but not a great deal.

Results were considerably different for MALPEs, which ranged between −7% and +14% (with most falling between −5% and +5%). All methods had positive errors for launch years 1910, 1930, 1960, and 1980 and negative errors for launch years 1940, 1950, and 1970; all except EXPO had negative errors for launch year 1920. These data reflect a high degree of variation from one launch year to another, but do not show any consistent trends over time or any general tendency for projections to be too high or too low.

The authors used statistical tests to evaluate stability over time in the means and variances of forecast errors. They concluded that there was a high degree of stability for the means and variances of absolute percent errors, somewhat less stability for the variances of algebraic percent errors, and no stability at all for the means of algebraic percent errors. Since the MALPE is a measure of bias, this implies that the study of past forecast errors can tell us little (if anything) about the likelihood that current projections will be too high or too low. However, the stability observed for the means and variances of absolute percent errors implies that the study of past errors can tell us something about the expected degree of accuracy of current projections.

Rayer et al. (2009) conducted a similar analysis of forecast errors for counties. Using several extrapolation methods and a sample of 2,482 counties with stable geographic boundaries between 1900 and 2000, they evaluated a series of

Table 13.6 Population forecast errors for U.S. counties by target year and length of horizon

Target year	Horizon	MAPE	MALPE
1930	10	12.2	2.2
1940	10	11.2	0.4
1950	10	11.2	2.9
1960	10	10.3	0.3
1970	10	9.6	−2.4
1980	10	13.2	−9.5
1990	10	7.8	4.0
2000	10	6.2	−3.5
Average	10	10.2	−0.7
S.D.	10	2.3	4.4
1940	20	20.2	5.9
1950	20	19.9	3.6
1960	20	23.0	6.4
1970	20	16.7	−0.5
1980	20	21.4	−12.1
1990	20	19.4	−9.3
2000	20	11.4	0.7
Average	20	18.9	−0.8
S.D.	20	3.8	7.3
1950	30	33.1	14.0
1960	30	32.9	8.5
1970	30	31.9	9.0
1980	30	22.9	−9.8
1990	30	29.3	−11.9
2000	30	27.8	−14.5
Average	30	29.5	−0.8
S.D.	30	4.2	12.6

Source: Rayer et al. (2009)

population projections with 20-year base periods; 10-, 20-, and 30-year horizons; and target years at 10-year intervals between 1930 and 2000. The results for the trimmed means are shown in Table 13.6. For MAPEs, there was a substantial degree of stability from one target year to another, albeit with some indication that errors have become smaller in recent decades. For MALPEs, no stability was apparent, as errors varied considerably from one target year to another.

Several other studies have compared forecast errors from different launch years. Keyfitz (1981) and Stoto (1983) focused on national-level projections; Kale et al. (1981) focused on projections for states; Smith (1987) focused on projections for counties; and Isserman (1977) focused on projections for townships. All found roughly the same results reported by Smith and Sincich (1988) and Rayer et al. (2009): Measures of accuracy were similar (but not identical) from one launch year to another, but measures of bias varied considerably. More research—covering a variety of projection methods, geographic regions, error measures, forecast horizons, and launch years—will help us refine these conclusions. Information on the stability of error distributions over time is crucial for the construction of empirical prediction intervals, a subject we turn to later in this chapter.

13.3 Projections of Demographic Characteristics

Many studies have evaluated forecast accuracy for projections of total population, but only a few have considered the accuracy of projections of demographic characteristics such as age, sex, race, or ethnicity. In a study of national population projections made between 1950 and 1980 in the Netherlands, Keilman (1990) found errors to be greatest for the youngest and oldest age groups. Projections were generally too high for the youngest age groups and too low for the oldest, indicating that forecasters underestimated future declines in fertility rates and increases in survival rates for the elderly. Keilman (1999) evaluated projections made by the United Nations between the 1950s and 1980s for seven regions in the world. He again found that errors were generally largest for the youngest and oldest age groups, although the direction of error was not the same in every region.

The results presented by Keilman were based on analyses of national and regional projections, where migration typically plays a small role in overall population change. Consequently, errors in projections of age structure were caused primarily by errors in the mortality and fertility assumptions. For states and local areas, however, migration is the most volatile component of population change and is the major determinant of differences in growth rates (Kulkarni and Pol 1994; Long and McMillen 1987; Nakosteen 1989). As a result, errors for states and local areas are likely to be largest in the young adult age groups because those age groups typically have the highest migration rates.

Smith and Shahidullah (1995) evaluated 10-year projections for census tracts in three counties in Florida. They found that MAPEs ranged from 20% to 29% for individual age groups and were generally largest for ages 25–34 and 65+. The results for ages 25–34 are not surprising, nor are the results for age 65+ when one recalls that Florida is a retirement state with high levels of elderly migration. On average, MAPEs for individual age groups were about 40% larger than the MAPE for the population as a whole (17.6%).

Smith and Tayman (2003) evaluated a series of age-group projections at the national, state, and county levels in the United States. At the national level, they found that errors for projections produced between the 1950s and 1980s were generally largest at the youngest ages, reflecting the difficulty of projecting fertility rates during periods when those rates were changing rapidly. This result is similar to that reported by Keilman (1990, 1999).

For state projections produced during the 1970s, 1980s, and 1990s, they found that MAPEs tended to be largest for the <5 and 25–34 age groups, reflecting the difficulty not only of projecting fertility rates but also projecting migration rates. On average, MAPEs for individual age groups were typically 10–30% larger than MAPEs for the total population.

For counties in Florida, they found that MAPEs were generally largest in the 25–34 age group. However, they also found relatively large errors in the 55–64 and 65+ age groups. This is similar to the results reported by Smith and Shahidullah (1995). On average, MAPEs for individual age groups were 45–55% larger than MAPEs for the total population. They concluded that the impact of migration on population change becomes larger as the geographic unit becomes smaller.

For short projection horizons, Smith and Tayman (2003) found that errors for particular age groups were sometimes two, three, or even four times larger than for other age groups. They noted, however, that cohorts pass through succeeding age groups as the projection horizon becomes longer, experiencing the error characteristics of each group as they do so. Relatively large and small errors are thus averaged together, causing differences in errors among age groups to become smaller. They speculated that for very long horizons, forecast errors are likely to be about the same for all age groups.

An interesting question is whether differences in methodological complexity might have a greater impact on forecast accuracy for projections of demographic characteristics than for projections of total population. Long (1995) provided one answer to this question by comparing two sets of national population projections: the Census Bureau's cohort-component model and a simple model in which the exponential growth rate for each age group in the year immediately prior to the launch year was extrapolated into the future. Focusing on two age groups (15–19 and 60–64), he found errors for 10-year projections to be much larger for the exponential extrapolations than for the cohort-component projections. He concluded that cohort-component models are more accurate than simpler methods for projecting population by age group.

We believe a better simple model can be constructed by using a decade rather than a single year as the base period and by extrapolating by cohort rather than by age group (Hamilton and Perry 1962). This model is discussed in Chaps. 6 and 7. Although it breaks the population into age groups, it is still a simple model, requiring only data by age (or age and sex) in two consecutive censuses rather than age-specific fertility, mortality, and migration rates and assumptions regarding future changes in those rates. This model incorporates the effects of population momentum and provides projections of the demographic characteristics of a population, making up for two of the major shortcomings of simple extrapolation methods.

Using data for states and for counties in Florida, Smith and Tayman (2003) compared age-group projections based on the Hamilton-Perry method with those based on more complex cohort-component models. They found the forecasting performance of the simpler Hamilton-Perry method to be very similar to that of the more complex models. Once again, a simple method was found to produce forecasts that were every bit as accurate as those produced by a more complex method.

We are not aware of evaluations of forecast accuracy for projections of racial, ethnic, and other characteristics of the population. Such evaluations—along with further research on the accuracy of age projections—would provide interesting and useful information.

13.4 Combining Forecasts

A common finding in the general forecasting literature is that a combination of forecasts often leads to greater accuracy and less variability than can be achieved using individual forecasts by themselves (Armstrong 2006; Crone et al. 2011; Hendry and Clements 2004; Makridakis and Hibon 2000; Webby and O'Connor 1996). This result has been found for many types of forecasts, including gross national product, inflation, corporate earnings, stock prices, exchange rates, electricity demand, tourism, psychiatric diagnoses, rainfall, and sunspot cycles. Why might this be true?

Theoretically, the best model should provide the most accurate forecasts. However, statistical models are based on the assumption that data patterns and mathematical relationships remain constant over time. This is rarely the case. Consequently, models that fit the data well during the base period do not necessarily provide accurate forecasts, and models that provide the best forecasts for one time period do not necessarily provide the best forecasts for other periods (Armstrong 2001b; Fildes 1992; Makridakis 1986; Pant and Starbuck 1990).

Combinations of forecasts work well for several reasons. First, each individual method and data set provides potentially useful information; using several forecasts thus increases the total amount of information going into the final forecast. Second, offsetting errors tend to cancel each other out, meaning that a combined forecast has a smaller risk of making a large error than an individual forecast. Finally, it is important to note that—even though combined forecasts do not outperform every individual forecast in every situation—there is no way to know in advance *which* of the individual forecasts (or forecasters) will perform better or worse than the combination for a particular set of forecasts. A number of empirical studies have concluded that combined forecasts are generally more accurate than most (sometimes all) of the individual forecasts making up the combination (Armstrong 2001a; Becker and Clements 2008; He and Xu 2005; McNees 1992; Schnaars 1986; Zarnowitz 1984).

Combining can be done in a number of ways. Individual forecasts can be based on different methods or different specifications of the same method. Combinations can incorporate the effects of many individual forecasts or only a few. They can be averages in which each individual forecast is weighted equally (i.e., a simple average); averages in which the highest and lowest individual forecasts are excluded (sometimes called a trimmed mean); or averages in which some forecasts are weighted more heavily than others. For weighted averages, weights can be based on objective criteria such as previous forecasting performance or on subjective criteria such as the personal judgment of experts.

There is no consensus in the literature regarding the best way to combine forecasts. Bates and Granger (1969) suggested the use of weights based on the size of errors found in previous applications of the individual forecasting techniques. Although some researchers have found weighted averages to produce more accurate forecasts than simple averages (e.g., Ashton and Ashton 1985; Hoogerheide et al. 2010), there is no guarantee that weights found to be optimal in the past will prove to be optimal in the future. Given this uncertainty, many researchers have concluded that a simple average or trimmed mean will generally perform at least as well as more sophisticated weighted averages (Armstrong 2001a; Genre et al. 2013; Hendry and Clements 2004; Pant and Starbuck 1990; Stock and Watson 2004).

How many individual forecasts should be used in combining? Some empirical investigations have used only two while others have used 20 or more. The consensus in the general forecasting literature seems to be that the greater the number of individual forecasts, the better (Granger 1989; Makridakis and Winkler 1983; Webby and O'Connor 1996). However, a large part of the improvement in performance comes with the first four or five forecasts included in the combination; further additions result in smaller and smaller improvements. It appears that many of the benefits of combining can be achieved with a relatively small number of individual forecasts (Armstrong 2001a; Ashton and Ashton 1985; Clemen 1989).

Although combining has been a common practice among forecasters for many years, demographers have been slow to embrace it for the production of population projections. Why might this be true? There are several possible explanations. One is the longstanding tradition in demography of producing sets of illustrative projections rather than a single forecast. If projections are intended simply to illustrate the outcomes of various combinations of assumptions, there is no need to consider various combinations of projections (or to be concerned with forecast accuracy, for that matter). Another explanation is that the dominance of the cohort-component method in official population projections has prevented demographers from investigating other methods. A third explanation is that demographers have been searching for one "true" model of population change and are unwilling to give up that quest. Using a combination rather than a single forecast may be viewed as an admission that the analyst has been unable to build a properly specified model.

Whatever the explanation, we believe combining offers the same potential benefits to population projections that have been achieved in other fields. Combining could be done using projections from several methods, including cohort-component, structural, and microsimulation models as well as various extrapolation methods, or it could be done using several alternative sets of assumptions for a given method (e.g., different combinations of mortality, fertility, and migration assumptions for cohort-component projections). It could be done using simple averages, trimmed means, or weighted averages based on historical observations or professional judgment. Multiple regression analysis could be used to uncover statistical regularities and to estimate optimal weights. Many approaches are possible.

It should be noted that some demographers have shown an interest in the potential benefits of combining. Voss and Kale (1985) made projections for minor civil divisions in Wisconsin using 11 extrapolation techniques. In evaluating forecast errors over a 10-year horizon, they found that the average of all 11 techniques had smaller errors than the majority of the individual techniques, and that no single technique consistently outperformed the average. Isserman (1993) made cohort-component projections for counties in West Virginia, using migration rates based on an average of rates from two decades. Ahlburg (1999) found that combining projections of births from an economic-demographic model with projections from the Census Bureau's cohort-component model improved the forecast accuracy of the cohort-component model. Sanderson (1999) found that averaging projections from structural models with projections from extrapolative models often led to more accurate forecasts than could be achieved by relying on a single model. Shang (2012) found that averaging forecasts of life expectancy from a number of time series models led to improved forecast accuracy.

One approach to combining that may prove to be particularly useful is the "composite" method described by Isserman (1977). This method is based on the assumption that some models or techniques perform substantially better (or worse) than others under particular circumstances or for places with particular characteristics. If consistent patterns can be observed with enough regularity to draw general conclusions, forecasts for particular places can be based solely on the models or techniques found to be most accurate for places with those characteristics.

Empirical evidence shows that the EXPO method often performs poorly for rapidly growing places and the SHIFT method often performs poorly for places with low or negative growth rates. This evidence—drawn from projections covering various time periods and different levels of geography—suggests that EXPO should not be used for projections of rapidly growing places and SHIFT should not be used for projections of places losing population. Smith and Shahidullah (1995) tested the composite approach by constructing an average that excluded EXPO projections for rapidly growing places and SHIFT projections for slowly growing or declining places. They found the composite approach to produce more accurate forecasts for census tracts than could be achieved using an average of all methods. Rayer and Smith (2010) evaluated a variety of projection methods for subcounty areas in Florida and found the composite approach to produce more accurate forecasts than any of the individual methods, simple averages, or trimmed means. We believe that looking for methods that work particularly well (or poorly) in particular situations will lead to greater improvements in forecast accuracy than could be achieved by looking for the method that performs best in all situations.

13.5 Accounting for Uncertainty

There is no uncertainty regarding the production of illustrative population projections. Unless a mathematical error is made in the underlying calculations, illustrative projections are exact representations of the hypothetical future population. For population projections used as forecasts, however, the story is very different. As our preceding discussion has shown, population forecasts entail a tremendous amount of uncertainty, especially for long time horizons and for places with small or rapidly changing populations. About the only thing we know for sure is that our forecasts are going to be wrong. If we are good forecasters—and lucky—the errors will be small. If we are not so good—or not so lucky—the errors may be huge.

How can we deal with this uncertainty? Two basic approaches have been used in the past. One is to produce several alternative projections or scenarios based on different methods or sets of assumptions. The other is to develop statistical prediction intervals based on historical data. Each approach has its strengths and weaknesses.

13.5.1 Alternative Scenarios

The traditional approach to dealing with uncertainty has been to construct several alternative sets of projections. These alternative scenarios can be based on the application of different projection methods, but a more common practice is to apply different sets of assumptions using the cohort-component method. This approach has a long history (Thompson and Whelpton 1933; Whelpton et al. 1947) and has been an integral part of the Census Bureau's state and national projections for many years. It has been widely used by state and local demographers as well. Among the producers of "official" population projections, constructing a range based on alternative sets of assumptions is the most common way to deal with uncertainty.

Alternative scenarios are typically developed using various combinations of mortality, fertility, and migration assumptions. For example, one set of U.S. projections used three assumptions for each of the three components of population growth, yielding 27 different projection series (Spencer 1989). Making an additional assumption for foreign immigration brought the total to 30. For the year 2080, these projections ranged from 185 to 501 million.

Most sets of projections do not contain nearly as many alternative scenarios. National projections generally have 10 or fewer series; indeed, some have had only three (U.S. Census Bureau 1950). An early set of state projections had four alternative series, based on combinations of two fertility assumptions and two migration assumptions for each state (U.S. Census Bureau 1966). A more recent set had only two, one based on a time series model of migration and the other based on an economic model of migration (Campbell 1996). There are exceptions, but the most common practice is to construct two, three, or four series when producing alternative projection scenarios.

Two interpretations can be given to the individual series in a set of alternative projections. One is that each series gives a reasonable view of future population change and that no particular series is any better than any other. This is the interpretation given to the Census Bureau's state projections from the 1950s to the early 1990s (U.S. Census Bureau 1957, 1966, 1972, 1979; Wetrogan 1990). Not only did Census Bureau analysts decline to designate a "preferred" or "most likely" series, but they took great pains to emphasize that the projections were not intended as to be used as forecasts or predictions. Of course, most data users promptly disregarded those warnings and chose a particular series (typically the middle one) as the forecast.

The second interpretation is that although each series provides a reasonable view of the future, one particular series is preferred to all others. The designation of a "preferred" or "most likely" series can be based on an empirical investigation of past forecast errors or on a subjective evaluation of the assumptions used in producing each series. This is the interpretation given to the state projections produced by the Census Bureau during the 1990s (Campbell 1994, 1996). In these projections, one particular series was designated as "preferred" and the others were simply alternatives. The Census Bureau's most recent state projections, however, contained only a single series and specified that the projections were not intended to be used as forecasts of future population trends (U.S. Census Bureau 2005).

There are also several interpretations of the range of projections itself. One is that the highest and lowest series provide a "reasonable" range around the preferred series. It is expected that the range will contain the future population observed in the target year, although no specific probability statements are made (Whelpton et al. 1947; U.S. Census Bureau 1950). Another is that the series making up the highest and lowest projections simply provide alternative views of the future. Under this interpretation, there are no stated expectations that the range will contain the future population (U.S. Census Bureau 1957).

The assumptions for mortality, fertility, and migration used in each projection series are typically based on historical values and the analyst's views regarding reasonable future changes in those values. However, the highest and lowest series in the range generally are *not* based on the highest and lowest levels each component of growth could feasibly reach. Consequently, there is no guarantee that the projected range will encompass the future population. In fact, several studies have reported that subsequent populations often fall outside the projected range (Alho and Spencer 1997; Keyfitz 1981; Stoto 1983). It has also been found that the range of individual point forecasts produced by several different projection methods provides a poor indicator of uncertainty. A range constructed in this manner typically understates the true level of uncertainty, sometimes by a substantial margin (McNees 1992).

Forecast uncertainty can also be assessed by comparing more broadly defined projection scenarios (Tayman 2011). For example, scenarios can be based on alternative assumptions regarding land use patterns, the transportation system, housing and transportation policies, the environment, and social equity factors. Under this approach, uncertainty is evaluated by considering various policy options; it is not intended to show a specific range of values for a particular area. One such evaluation compared 2030 forecasts for San Diego County assuming current land use plans, which constrain housing production, with an unconstrained housing forecast (San Diego Association of Governments 2006). The results showed that restricting housing production resulted in larger household sizes, fewer population-serving jobs, upward pressure on homes prices, a very low vacancy rate, and an increase of 100,000 more commuters from outside the county. This approach is a relatively benign way to illustrate forecast uncertainty to data users. It is not likely to raise questions about staff or model credibility because the focus is on "what if" questions rather than on precise measures of uncertainty (Tayman 2011).

Producing alternative scenarios has several benefits. One is that it makes it easy to observe the effects of differences in assumptions. For example, suppose that two series are based on identical mortality and migration assumptions, but one assumes that fertility rates will increase by 10% while the other assumes that fertility rates will fall by 10%. Differences in population size and age structure caused solely by differences in fertility rates can easily be determined by comparing these series. Outcomes from other combinations of assumptions can also be compared.

Another benefit is that alternative scenarios give the data user several options from which to choose. Because each series is based on clearly defined mortality, fertility, migration or other assumptions, the data user can make choices based on his/her judgment regarding the validity of those assumptions. This will be particularly important when the data user has a high level of technical expertise and knowledge of the area being projected. Of course, if the data user lacks knowledge and expertise, this benefit will be lost.

The primary limitation of producing a range of projections based on alternative scenarios is that it does not provide an explicit measure of uncertainty. How likely is it that any particular series will provide an accurate forecast of future population change? How likely is it that the future population will fall within the range suggested by two alternative series? These questions cannot be answered simply by producing a range. Alternative scenarios may provide several reasonable views of the future, but they do not provide data users with a clear idea of the degree of uncertainty surrounding a population forecast.

13.5.2 Prediction Intervals

The second approach focuses on statistical measures of uncertainty. Prediction intervals based on statistical theory and data on error distributions provide an explicit estimate of the probability that a given range will contain the future population. These intervals are sometimes called *forecast intervals*, *probability* *intervals*, *confidence intervals*, or *confidence limits*. We call them *prediction intervals* to distinguish them from traditional confidence intervals which—strictly speaking—apply only to sample data.

Two types of prediction intervals have been used most frequently for population forecasts. One is based on the development of statistical models of population growth and the other is based on empirical analyses of errors from past population projections. Both rely on the assumption that historical or simulated error distributions can be used to predict future error distributions.

13.5.2.1 Model-Based Intervals

Model-based prediction intervals capitalize on the stochastic (or random) nature of population processes. They can be developed in a number of ways. Past applications have included maximum likelihood estimators of population growth rates (Cohen 1986); Monte Carlo simulations of fertility and migration rates (Pflaumer 1988); regression-based projection models (Swanson and Beck 1994); Bayesian projection models (Alkema et al. 2011); models based on the opinions of a group of experts (Lutz et al. 1999; San Diego County Water Authority 2002); and time series models covering mortality rates (Lee and Carter 1992), life expectancy (Torri and Vaupel 2012), fertility rates (Lee 1993), net migration (de Beer 1993), and total population size (Alders et al. 2007; Hyndman and Booth 2008). Although much of the research on model-based intervals has focused on national or regional projections, recent research has extended the analysis to subnational projections as well (Cameron and Poot 2011; Tayman et al. 2007; Wilson and Bell 2004).

Time series models (especially ARIMA models) are the models most commonly used for developing prediction intervals for population projections. These models assume that the pattern (structure) of the data does not change over time, that errors are normally distributed with a mean of zero and a constant variance, and that errors are independent of each other (Makridakis et al. 1987). Time series models require a fairly long series of historical observations and can be difficult to apply, especially when attempting to combine prediction intervals for all three components of growth and developing intervals for various subgroups of the population.

Providing a detailed description of model-based prediction intervals is beyond the scope of this book, but we can give several examples of the intervals produced by these models and compare them to the high and low projection series produced using the traditional approach. Lee and Tuljapurkar (1994) projected a population of 398 million for the United States in 2065, with a 95% prediction interval of 259–609 million. This range is wider than the spread between the low and high projections produced by the Census Bureau at about the same time; those projections ranged from 276 to 507 million in 2050, with a medium projection of 383 million (Day 1992). The previous set of Census Bureau projections reported much lower numbers and a slightly smaller range, with a medium projection of 300 million and a range of 230–414 million for 2050 (Spencer 1989).

Pflaumer (1992) made two time series projections of the U.S. population, one based on population size and the other based on the natural logarithm of population size. The first model produced a medium projection of 402 million in 2050, with a 95% prediction interval of 277–527 million. These numbers are similar to the Census Bureau's projections from the same time. The second model produced a medium projection of 557 million, with a 95% prediction interval of 465–666 million. These numbers are much higher and provide a narrower range than the Census Bureau's projections.

McNown et al. (1995) made time series projections of the components of growth for the U.S. population, as well as total population size. For 2050, they projected a total population of 373 million, with a 95% prediction interval ranging from 243 to 736 million. The total fertility rate was projected to be 2.46 in 2050, with a 95% prediction interval ranging from 0.91 to 5.53. Life expectancy at birth for males was projected to be 75.5, with a 95% prediction interval ranging from 68.5 to 82.8. For fertility these intervals are much larger than those found in the Census Bureau projections, which assumed that the total fertility rate would range only from 1.83 to 2.52 in 2050 (Day 1992). For mortality the intervals are not much different than those reported by the Census Bureau, in which life expectancy at birth was projected to range between 75.3 and 87.6 in 2050.

Swanson and Beck (1994) developed a regression-based model for making short-term county population projections in the state of Washington. They compared the 2/3 prediction intervals associated with this model to census counts of Washington's 39 counties in 1970, 1980, and 1990. They found the prediction intervals to contain the 1970 census count in 30 counties (77%), the 1980 census count in 24 counties (62%), and the 1990 census count in 31 counties (79%). These results suggest that Swanson and Beck's 2/3 prediction intervals provided a reasonably accurate view of forecast uncertainty.

Model-based prediction intervals are valid only to the extent that the assumptions underlying the models are valid. In spite of their objective appearance, they are strongly influenced by the analyst's judgment. The models themselves are often complex and require a substantial amount of base data. They are subject to errors in the base data, errors in specifying the model, errors in estimating the model's parameters, and future structural changes invalidating the model's parameter estimates (Lee 1992). In addition, alternative forecasting models can be specified, each providing different (perhaps dramatically different) prediction intervals (Cohen 1986; Lee 1974; Tayman et al. 2007).

In spite of these problems, model-based prediction intervals offer one important benefit: they provide explicit probability statements to accompany point forecasts. The intervals are often wide, exceeding the low and high projections produced by official statistical agencies. Given that many data users (and producers) tend to overestimate the accuracy of population projections, model-based prediction intervals provide an important reality check.

13.5.2.2 Empirically-Based Intervals

The second type of prediction interval is based on empirical analyses of errors from past projections. Keyfitz (1981) took some 1,100 national projections made between 1939 and 1968 and, for each one, calculated the difference between the projected annual growth rate and the rate actually occurring over time. He found this difference to be largely independent of the length of horizon over which the projections were made. He calculated the RMSE for the entire sample to be approximately 0.4 percentage points and developed 2/3 prediction intervals by applying that error to the growth rates projected for each country. For example, if a country were projected to grow by 2% per year for the next 20 years, the probability would be approximately 2/3 that the actual growth rate would be somewhere between 1.6% and 2.4%.

Keyfitz refined his analysis by separating countries according to their population growth rates, finding a RMSE of 0.60 for rapidly growing countries, 0.48 for moderately growing countries, and 0.29 for slowly growing countries. He illustrated this refinement by applying the 0.29 RMSE to the U.S. growth rate of 0.79% per year projected by the Census Bureau, yielding annual growth rates of 0.50% and 1.08%. Applying those growth rates to the 1980 population of 260 million produced a range of 245–275 million in 2000. He concluded that the odds were about 2 to 1 that this range would contain the U.S. population in that year.

Stoto (1983) followed a similar approach, but analyzed projections containing more temporal and geographic diversity. Like Keyfitz, he calculated forecast error as the difference between the projected annual growth rate and the rate actually realized over time. He differentiated between two components of error, one related to the launch year of the projection and the other to seemingly random events (the residual). For more developed countries, he found the launch-year component to have a distribution that was stable over time and centered around zero, implying that the projections were unbiased. For less developed countries, he found the variance of the launch-year component to be stable but that earlier sets of projections had a strong downward bias (although recent sets had little bias). The second component (the residual) was found to have a stable distribution but to have occasional outliers. For both components, the variance was larger for less developed countries than more developed countries.

Stoto calculated the standard deviations for these two components of error and constructed prediction intervals in a manner similar to that used by Keyfitz. He applied those intervals to projections of the U.S. population and estimated that there was about a 2/3 probability that an interval of 241–280 million would contain the actual population in 2000, and a 95% probability that an interval of 224–302 million would contain that population. He compared his results to projections produced by the Census Bureau, concluding that the Census Bureau's low and high series were very similar to a 2/3 prediction interval. Keyfitz (1981) had reached the same conclusion.

Smith and Sincich (1988) also used the distribution of past forecast errors to construct prediction intervals, but followed a different approach. They modified a technique developed by Williams and Goodman (1971), in which the predicted distribution of future forecast errors was based directly on the distribution of past forecast errors. An important characteristic of this technique is that it can accommodate any error distribution, including the asymmetric and truncated distributions typically found for absolute percent errors.

Using population data for states from 1900 to 1980, Smith and Sincich used four simple extrapolation methods to make a series of projections covering 10- and 20-year horizons. They calculated absolute percent errors for each target year by comparing projections with census counts, focusing on the 90PE for each set of projections (i.e., the absolute percent error larger than exactly 90% of all absolute percent errors). They investigated two approaches to constructing 90% prediction intervals, one using the 90PE from the previous set of projections and the other using the 90PE from all other sets of projections. They found both approaches to provide relatively accurate prediction intervals. For most individual target years, 88–94% of state forecast errors fell within the predicted 90% interval. Summing over all target years, 91% of all forecast errors fell within the predicted 90% interval. They concluded that stability in the distribution of absolute percent errors over time made it possible to construct useful prediction intervals for state projections.

Rayer et al. (2009) used the Williams & Goodman approach to construct and test prediction intervals for a large sample of counties in the United States. Using data by decade from 1900 to 2000, they constructed county forecasts covering 10-, 20-, and 30-year horizons and calculated forecast errors for each target year. Although the center of the algebraic error distributions shifted considerably from one decade to the next, the shape remained relatively constant over time. They evaluated the performance of 90% prediction intervals based on the distribution of absolute percent errors and found that—aggregated over all decades—errors for 91% of the counties fell within the prediction intervals for all three horizons. Although there was some variation from decade to decade, the proportion of errors falling within the intervals was usually between 88% and 93% and never varied by more than 10 percentage points.

Smith and Rayer (2012) followed a similar approach in testing prediction intervals for county projections in Florida. Using forecast errors for target years 1985, 1990, and 1995, they constructed 2/3 prediction intervals for projections with launch years 1995, 2000, and 2005 and counted the number of counties in which the subsequent population counts or estimates fell within the predicted intervals. They found that 43 counties (64%) fell within the predicted range for 5-year horizons and 49 counties (73%) for both 10- and 15-year horizons. These numbers were fairly close to the 45 counties implied by the prediction intervals. Given the year-to-year volatility of Florida's population growth, this reflects a reasonably good forecasting performance.

Tayman et al. (1998) developed statistically-based prediction intervals for subcounty population forecasts in San Diego County. They started by projecting the population residing in grid cells, which are geographic areas of 2,000 ft. by 2,000 ft. defined for the most densely populated parts of the county. The projections had 1980 as a launch year and 1990 as a target year. Using repeated sampling techniques and randomly selected grid cells, they developed projections for a large number of areas varying in size from 500 to 50,000. Forecast errors were calculated by comparing the 1990 projections with 1990 census counts.

Rather than constructing prediction intervals for the population forecasts per se, Tayman and his colleagues developed predictions for the mean errors implied by those forecasts. Empirical prediction intervals for MAPEs and MALPEs were developed using an approach similar to that used by Williams and Goodman (1971) and Smith and Sincich (1988). For areas with 500 persons, they found a 95% prediction interval of 67.4–80.3% for the MAPE. For areas with 50,000 or more, the interval was 9.7–11.5%. For MALPE, the intervals were wider but centered closer to zero.

13.5.2.3 Evaluating the Evidence

Under formal definitions, probability statements about the accuracy of population projections cannot be made because the distribution of future forecast errors is unknown (and unknowable) at the time projections are made. However, it is possible to construct prediction intervals based on specific models of population change or on the distribution of errors from past projections. If current projection methods are similar to those used in the past, and if the degree of uncertainty is about the same in the future as it was in the past, then we can assume that future forecast errors will be drawn from the same distribution as past forecast errors (Keyfitz 1981). If this is true, prediction intervals will provide a reasonable (albeit imperfect) view of the uncertainty surrounding current population projections.

The critical question, of course, is whether the distribution of forecast errors does indeed remain stable over time. Smith and Sincich (1988) showed that the distribution of absolute percent errors for states remained relatively stable over the decades of the twentieth century; Rayer (2009) and Smith and Rayer (2012) reported similar results for counties. Stoto (1983) divided forecast errors into two components and found the distributions of both components to remain fairly stable over time for national projections made between the 1940s and the 1970s. Some empirical evidence, then, supports the notion that the distribution of population forecast errors remains relatively stable over time.

More research is needed on how to construct and interpret population prediction intervals. Which approach is best? What are the effects of differences in projection method, launch year, geographic region, and length of horizon? How can intervals be developed for demographic subgroups (e.g., age, sex, race) that are consistent with each other and with intervals for the entire population? Much remains to be done, but the potential pay-off is high. Although we may never be able to forecast a specific *population* with a high degree of accuracy, we may be able to develop relatively accurate forecasts of the *distribution of errors* surrounding our population forecasts. Providing a realistic estimate of the uncertainty inherent in population forecasts may be the most useful service the producers of population projections can provide to their users.

13.6 Conclusions

To close this chapter, it may be helpful to summarize the empirical evidence regarding forecast accuracy and bias for population projections. Forecast accuracy generally increases with population size but tends to level off among larger places. It tends to be greatest for places with slow but positive growth rates and decline as growth rates deviate in either direction from those levels. Errors for individual places vary substantially from one launch year to another, but the distribution of absolute percent errors tends to remain fairly stable over time. Mean absolute percent errors grow about linearly with the projection horizon but mean algebraic percent errors follow no consistent pattern. For long-range projections based on simple extrapolation methods, 10 years of base data are generally necessary (and sufficient) to maximize forecast accuracy but 20 years may be needed for some methods (e.g., EXPO). For projections of total population no single model or technique is consistently more accurate than any other. Averages of several forecasts are often more accurate than individual forecasts. These results have been found so frequently that we believe they can be accepted as general characteristics of population forecast errors.

No general conclusions can be drawn regarding the direction of forecast errors. Some individual projections have large positive errors, others have large negative errors. Some sets of projections exhibit a substantial upward bias, others exhibit a substantial downward bias. There is no way to know in advance whether a particular projection (or set of projections) will be too high or too low. Over time, positive and negative errors seem to be roughly in balance. In this sense, we believe most population projection methods are unbiased.

What level of error might a data user expect from a set of population forecasts? Using the evidence cited in this chapter, and assuming that MAPEs grow about linearly with the projection horizon, we have developed a set of "typical" MAPEs by level of geography and length of horizon (Table 13.7). For states, MAPEs grow from 3% for 5-year horizons to 18% for 30-year horizons; for counties, they grow from 6% to 36%; and for census tracts, they grow from 9% to 54%. Errors for any specific set of projections will be affected by factors such as projection method, population size, growth rate, and launch year, of course, but we believe these numbers provide reasonable ballpark estimates of likely forecast errors.

These errors illustrate the high degree of uncertainty inherent in population projections, especially for small areas and for long projection horizons. Data users should be aware of these errors before making decisions based on population projections. Projections that extend very far into the future simply cannot provide highly accurate forecasts. This may be disheartening news for the users of

Table 13.7 "Typical" MAPEs for population projections by level of geography and length of horizon

Level of geography	Length of projection horizon (Years)					
	5	10	15	20	25	30
State	3	6	9	12	15	18
County	6	12	18	24	30	36
Census tract	9	18	27	36	45	54

population projections, but it is a realistic portrayal of forecast accuracy, given the current state of the art.

Given this high degree of uncertainty, why should an analyst even bother making small-area projections? There are several reasons. First, the projection process itself is educational. It teaches a great deal about the area(s) being projected, including the stability of geographic boundaries over time, historical demographic and socio-economic trends, special population subgroups, the occurrence of unique or unusual events, and the potential impact of growth constraints. The process of collecting and analyzing data provides insights that deepen the analyst's understanding of the population dynamics of the projection area(s).

Second, projections are useful for evaluating demographic scenarios. What impact would a 10% decline in the total fertility rate have on the age structure of the population? How would the continuation of recent in- and out-migration rates affect future levels of net migration? What would be the demographic impact of the opening of a new factory employing 2,500 workers? Projection models are useful for answering a broad array of analytical questions and for providing an indication of the range of future possibilities. The ability to trace out the implications of particular scenarios is a valuable tool in planning for (or attempting to influence) future population trends.

Finally—and perhaps most important—there is really no alternative to making population projections. If one is not willing to make projections, he/she must either ignore potential change or assume that no change will occur. Neither of these options is particularly attractive. Ignoring potential change is not likely to be helpful in most circumstances; ignorance generally is *not* bliss. Furthermore, the assumption that no change will occur is itself a projection, albeit a naïve and often ill-founded one. Projections based on no-change assumptions often lead to less accurate forecasts than could be obtained using other projection methods, especially for large or rapidly growing places (Tayman 1996). Although population forecasts are almost always in error—sometimes by a wide margin—they represent our best hope of planning intelligently for the future.

Forecast accuracy is a very important characteristic of population projections, but it is not the only criterion upon which projections should be judged. In the final analysis, projections can best be judged on the basis of their overall "utility," or their value in improving the quality of information upon which decisions are based (Swanson and Tayman 1995). Even though they cannot provide perfect predictions of future population trends, projections can point to potential growth constraints, highlight areas that are likely to lose population or grow very rapidly, show the implications of alternative public policy or land use decisions, and play other useful roles (Tayman 1996).

Do projections provide a stronger basis for decision-making than the alternative, which is to *not* make projections? If so, are the gains large enough to offset the costs of making those projections? If these two questions can be answered affirmatively, population projections can play an important role in planning and analysis in spite of their sometimes less-than-stellar performance as forecasts.

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Chapter 14
A Practical Guide to Small-Area Projections

We have provided a great deal of information on the construction and evaluation of population projections in this book, covering the most commonly used projection methods, potential data sources, criteria for evaluating projections, and characteristics of forecast errors. All this information may have left the reader feeling a bit intimidated or perhaps completely overwhelmed. How can a demographer, planner, market researcher, or other analyst proceed when called upon to construct a set of population projections?

In this chapter, we present a set of guidelines we hope will alleviate some of this apprehension and anxiety (see Box 14.1). These guidelines are intended as a summary of the material presented throughout the book and as a road map guiding the analyst through the projection process. They will not provide answers to every question, of course, but at least they will provide a checklist highlighting the issues that must be considered and the choices that must be made. We believe they will help the analyst make reasonable choices and—perhaps more important—avoid potentially disastrous pitfalls.

These guidelines focus on projections for small areas (i.e., counties and subcounty areas) for two reasons. First, the demand for small-area projections is large and growing rapidly. They are used for planning when and where to build new schools, roads, hospitals, and shopping centers; whether to expand the capacity of an electric power plant or a public transportation system; how to tailor a marketing plan to fit the needs of a specific client; and how to balance population growth with environmental concerns. We believe this demand will continue to grow.

Second, population size and data availability create methodological problems for small-area projections that do not exist (or are much less severe) for projections of larger areas. Consequently, some issues that must be dealt with when making projections for small areas are not present when making projections for large areas. In spite of this focus on small areas, much of the discussion in this chapter is applicable to state and national projections as well.

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Box 14.1 How to Make Small-Area Projections

1. Determine what is needed
   - Demographic characteristics
   - Geographic regions
   - Length of horizon and projection interval
   - Time and budget constraints
   - Other considerations
2. Construct the projections
   - Choose projection method(s)
   - Collect and evaluate data
   - Adjust for special events
   - Control for consistency
   - Account for uncertainty
3. Review and document results
   - Internal review
   - External review
   - Documentation

14.1 Determine What is Needed and the Resources Available

The first step in the projection process is to determine exactly what is needed and the time and money available to complete the project. This may seem almost too obvious to mention, but clients (i.e., the persons, agencies, or organizations requesting the projections) are often unsure about what they really need and what the costs are likely to be. Consequently, it is essential to discuss all aspects of a project at the very beginning, covering the relevant details clearly and completely. It is also helpful to discuss the purposes for which the projections will be used. This will help the analyst determine the type of projections needed and choose the most appropriate data sources and projection methods.

The process will be different for general-purpose projections than for customized projections. General-purpose projections are those produced without reference to a specific use or data user, whereas customized projections are those produced for a single data user or a particular purpose. Decision-making criteria can be more clearly defined for customized projections than for general-purpose projections. Consequently, the decisions underlying general-purpose projections must be based on the analyst's expectations regarding the primary needs of the majority of data users. Time and budget constraints will play an important role in these decisions because the production of greater geographic and demographic detail requires greater resources.

Failing to clearly define all aspects of a project at the very beginning is an invitation to disaster, leading to wasted resources, unsatisfactory results, and unhappy clients. The following checklist will help the analyst identify the issues that must be resolved before starting the projection process.

14.1.1 Demographic Characteristics

Should the projections refer simply to total population size or also to characteristics such as age, sex, race, and ethnicity? If age-group projections are needed, what are the relevant age categories (e.g., 1-year groups or 5-year groups)? What racial or ethnic categories are needed? What types of cross tabulations are required? For example, if projections of the Hispanic population are needed, should they be made by age, sex, and race? The client will generally be able to answer these questions, but may not realize their importance unless prompted by the analyst. Knowing the purpose for which projections will be used helps determine which demographic characteristics are required.

Age, sex, race, and ethnicity are the characteristics most commonly included in population projections. For some purposes, however, projections of other characteristics or population subgroups may be needed. Examples include persons with disabilities, the institutionalized population, the seasonal population, persons in the labor force, school enrollment, and the number of commuters. The projection model may also be used to project the components of population growth (births, deaths, and migration). Again, knowing the purposes for which the projections are to be used helps determine the type of projections needed.

14.1.2 Geographic Areas

Population projections are often made for well-defined areas such as states and counties. The geographic boundaries for these areas are easy to determine, match up clearly with the boundaries used for tabulating many types of data, and generally remain stable over time. For subcounty areas, however, the situation may be very different.

Boundaries for subcounty areas are subject to sudden and dramatic changes. It is not uncommon for cities to annex adjoining areas, for census tracts to be subdivided, for ZIP code areas to be reconfigured, for service areas to be redefined, and for new school districts to be formed. The analyst must determine whether the boundaries of the area to be projected have changed during the period for which historical base data have been collected. If the boundaries have changed, the analyst must decide whether to try to account for future boundary changes or simply hold current boundaries constant. We believe it is generally advisable to hold current boundaries constant, but there may be circumstances in which accounting for potential future changes may be useful (e.g., projections for a city with a history of frequent annexations). If current boundaries are held constant, historical data must be adjusted to reflect a geographic area that remains constant over time; otherwise, historical changes in the base data will mix the effects of boundary changes and population changes, thereby confounding the projection process. If boundary changes have occurred but no relevant data are available, the analyst may have to make subjective adjustments based on anecdotal evidence or use projection methods requiring data from only one point in time (e.g., the constant share method).

Sometimes projections must be made for areas lacking well-defined boundaries. For example, a client may have only a rough idea of the geographic boundaries defining the service area for a hospital, automobile dealership, or retail establishment. In these instances, the analyst and client will have to work together to establish a clear set of boundaries. Customer records or a sample survey may help determine the relevant area. When delineating the boundaries of a geographic area, it is helpful to match boundaries with those used for tabulating historical base data (e.g., counties, cities, census tracts, or block groups). This will make it easier to collect reliable data.

Also, there may be circumstances in which the population to be projected is not defined geographically (e.g., the number of veterans from the armed forces or the number of retirees from a company). In these circumstances, of course, geographic boundaries are irrelevant (unless one is also concerned with the geographic distribution of that population, such as the number of veterans residing in New Jersey).

14.1.3 Length of Horizon and Projection Interval

What time span and projection intervals are needed? Should the projections extend for 5 years, 10 years, 20 years, or longer? Should they be made in 1-year, 5-year, or 10-year intervals?

Data availability plays an important role in the choice of projection interval. Annual data may be unavailable for some subcounty areas, making it difficult to make projections in 1-year intervals. Although data can be adjusted to match different time intervals, this process is subject to a number of problems (see the discussion of migration adjustments in Chap. 6). In most instances, we believe it is advisable to match projection intervals with the time periods for which data are available. For example, when using net migration data derived from two consecutive censuses, it is better to make projections using 10-year intervals than try to convert 10-year data into 1- or 5-year data. If annual projections are needed, they can be made by interpolating between target years (see Chap. 10).

14.1.4 Time and Budget Constraints

It is essential to start with a clear understanding of the time, money, and other resources available for developing the projections. This is true regardless of whether the client is an outside party or someone from within the analyst's own agency or organization. Indeed, many of the decisions made throughout the projection process will be affected by deadlines and available resources. In general, the greater the amount of demographic and geographic detail required and the greater the attention paid to an area's unique characteristics and special populations, the greater the time and other resources needed to construct the projections. An inadequate budget or too short a time frame will lead to low levels of quality (for the projections) and high levels of stress (for the analyst and the client).

It takes more time to construct a set of projections the first time than it does to repeat the process a second, third, or fourth time. Developing a projection model from scratch and collecting, analyzing, and adjusting input data are very time-consuming tasks. Updating a set of projections is much simpler. The best advice for first-time producers of population projections is the same as for someone about to remodel his/her kitchen: allow twice as much time as you think the project should take.

14.1.5 Other Considerations

A variety of other factors must be considered. Will the projections be used solely as forecasts or will they play other roles (e.g., trace out the effects of different assumptions or scenarios)? Do they need to be tied to some other type of projection (e.g., census tract projections controlled to an independent county projection)? Will they be subject to some type of review process? If so, what parties will participate in this process? Will those parties have a strictly advisory role or will they have the power to require changes in the methodology, assumptions, or results? If there are disagreements, how will they be resolved?

Political considerations may be particularly important. In some instances, the analyst has complete freedom to select methods and assumptions; in other instances, outside parties are involved (e.g., clients, government agencies, groups of data users). In these instances, it may be helpful to put together an advisory panel made up of representatives from each party. Members of this panel can provide input regarding geographic areas, data, techniques, assumptions, projection intervals, and so forth. This input is likely to improve both the quality and the political acceptability of the projections (Tayman 2011). Conflicts can be resolved more easily early in the production process than at the end. Even when not required by law, achieving consensus among major stakeholders may raise the credibility of the projections.

As discussed in Chap. 12, political considerations can have either a positive or negative impact on the quality of projections, depending on the specific circumstances involved. Independent analysts have the option of saying "no" to a project if they believe political influences will harm their professional reputations or compromise the integrity of the projections. Staff members working within a government agency or private business may not have this option; refusing to participate in a project or to accept non-technical input may be tantamount to handing in one's resignation. Clearly, political considerations can present the analyst with thorny ethical dilemmas.

14.2 Construct the Projections

14.2.1 Select Computer Software

The first step in constructing a set of projections is to select the computer software that will be used to organize and manipulate the input data, develop the projection algorithms, and present the projection results. Three broad types of software can be used: electronic spreadsheets (e.g., Excel, Google Docs, and Apache Open Office), statistical analysis packages (e.g., SAS, SPSS, and R), and customized routines written using computer programming languages (e.g., C++, Java, and Python). Several critical issues must be considered when selecting the appropriate software:

1. How does the software handle input data? The most useful software will be adept at handling data from multiple system platforms (UNIX, PC, mainframe, the cloud) and a variety of distribution media and file formats. Although many data files are now downloadable, some historical data series are available only in paper records, CDs, or even mainframe cartridges. File structures have become more complex as programmers seek to increase efficiencies related to machine readability and automatic data processing and hierarchical structures have become commonplace (e.g., PUMS data). The use of relational database managers (e.g., Access, Oracle, SQL) to store, retrieve, and manage information from large data sets can greatly facilitate the development of population projections, especially for detailed characteristics covering a large number of geographic areas.
2. How adept is the software at formulating and modifying the algorithms that will be used in constructing the projections? How does it handle the sequence of data transformations and modeling steps required by the projection model? Statistical analysis packages and formal programming languages perform these functions very well and can easily accommodate changes in data and statistical routines. Spreadsheets are somewhat unwieldy because changes in the number of observations or operations cannot be handled seamlessly. Rather, formulas or worksheets must be duplicated, adding to the workload and creating additional opportunities for error. Although the use of macros can substantially reduce

these problems, the drawbacks of spreadsheets become more acute with increases in the number of areas and level of demographic detail being projected.
3. How does the software present its output? Projection results are typically released as reports, tables, charts, and maps, in both hard-copy and computer-readable formats. Headers, footers, and appended notes must be programmed from scratch when a customized routine is used, but those functions are already included in most statistical packages and spreadsheets, along with relatively easy-to-use graphing and table-generating capabilities. Some software packages produce web-enabled files and generate a multi-purpose data warehouse capable of accepting queries from web browsers. This is very useful for disseminating projections data quickly and easily. In addition, providing metadata describing the structure, content, and context of data files greatly increases their usability and quality.

Off-the-shelf software packages for most population projection methods are very limited. For trend extrapolation and cohort-component projections, the few packages currently available are either difficult to use or are not flexible enough to make them applicable in a variety of settings and special circumstances. The only exception is structural models, for which some software packages are available (but expensive).

The analyst making population projections will generally have to write his/her own computer programs, using a spreadsheet, statistical analysis package, and/or programming language. We believe spreadsheets are particularly useful when the projections do not involve too many computations, but statistical analysis packages or programming languages are more useful when the projections cover a large number of areas or require complex programming. It should be noted that most of the computations, tables, and figures shown in this book were done using a spreadsheet program.

14.2.2 Choose Projection Method(s)

The next step is to choose the methods to be used for making the projections. This choice will depend on the purposes for which the projections will be used; the level of geographic and demographic detail needed; the amount of time, money, and other resources available; and the availability of relevant input data.

A variety of methods can be used for projections of total population. Simple extrapolation methods such as linear, exponential, shift-share, and share-of-growth will often be sufficient, especially for short-to-medium time horizons. The reader is reminded, however, of the potential problems of using the exponential method for places that grew rapidly during the base period or using the shift-share method for places that either grew or declined rapidly (see Chap. 13).

Simple extrapolation methods can also be used for projections of racial or ethnic groups, but projections by age will require some type of cohort approach. Although cohort-component models based on gross migration data are theoretically superior to models based on net migration data, the lack of reliable data often poses a serious problem for gross migration models (see Chap. 6 for further discussion). Net migration models have smaller data requirements, are easier to apply, and generally can be tailored to produce forecasts that are as accurate as those produced by gross migration models. Even the relatively simple Hamilton-Perry method provides reasonably accurate forecasts in many circumstances; this method is particularly useful for projections of subcounty areas. In order to avoid a tendency to over-project the populations of rapidly growing areas, however, it is advisable to control projections based on net migration models and the Hamilton-Perry method to independent projections of net migration or total population, at least in those areas.

Other considerations come into play as well. Projections made for purposes of simulation or policy analysis generally require the use of a cohort-component model and perhaps a structural or microsimulation model. Projections of population subgroups such as prison inmates, seasonal residents, or public school enrollees require models that specifically account for those subgroups.

An important point to remember when choosing a projection method is that no single model or technique is better than all others for all purposes. Rather, each has its own strengths and weaknesses and must be evaluated according to its face validity, timeliness, cost, data requirements, ease of application, and other characteristics. Some of these characteristics are complementary (e.g., low costs, low data requirements, and ease of application typically go together), but others conflict with each other (e.g., greater geographic and demographic detail imply greater time and money costs).

In the final analysis, the choice of projection method will be determined by the analyst's judgment regarding the optimal combination of these characteristics. As a general rule it is best to use the simplest method that can accomplish the task at hand. This allows the analyst to spend more time on activities that are likely to have an impact on the quality of the projections (e.g., checking for errors in the input data, adjusting for unique events, and reviewing the projection results), while spending less time on activities that are not likely to matter very much (e.g., developing an unnecessarily complex projection model). The reader is also reminded of the potential benefits of combining projections from a variety of methods, perhaps using different base periods or sets of assumptions (see Chap. 13). We believe combining is particularly valuable for small-area projections, where the potential for large errors is greatest.

14.2.3 Collect and Evaluate Data

The availability and quality of input data has a major impact on the choice of the projection method. Simple trend extrapolation and ratio methods only require total population data for two points in time (one point for the constant share method). Time series models require data for many points in time. The Hamilton-Perry method requires data by age and sex (and perhaps other characteristics) from two points in time. More complex cohort-component models require data on births, deaths, and migration and the demographic make-up of the population. Structural models require data on explanatory variables as well as dependent variables. Urban systems models require data on vacant land, zoning restrictions, employment, transportation systems, and similar variables. Microsimulation models require data on the activities of individual units such as persons, households, vehicles, organizations, or firms.

The lack of appropriate data may cause the analyst to choose a different method than would have been chosen under ideal circumstances. Population data are almost always available for at least two points in time (e.g., the two most recent censuses) but annual time series data are unavailable for many subcounty areas, making it difficult or impossible to use complex extrapolation methods. Fertility and mortality data are generally available for states and counties but are often unavailable for subcounty areas; detailed in- and out- migration data are difficult to obtain even for states and counties. When fertility, mortality, and migration data are not available, cohort-component projections can be made using the Hamilton-Perry method or model schedules (i.e., rates from another source thought to be representative of the projection area). Options are more limited when the data required by structural and microsimulation models are unavailable; in those circumstances, those models generally cannot be used.

Whatever methods are chosen, efforts must be made to obtain the most recent data available. The decennial census is an excellent source, providing data on total population and basic demographic characteristics down to the block level. For years after or between censuses, estimates of total population are often available. When such estimates are not available, they can be constructed using a variety of data sources and estimation techniques (Siegel 2002; Smith and Cody 2013; Swanson and Tayman 2012). Data on detailed demographic and socioeconomic characteristics can be obtained from the American Community Survey (ACS) but may contain large sampling errors for small areas. Using recent data is important because growth trends sometimes change rapidly, especially for small areas.

It is also important to evaluate the quality of the input data. Although it is the closest thing to a "gold standard" for demographic data in the United States, the decennial census is not error-free. Errors are often corrected within a year or two after the census, but they sometimes go uncorrected until the following census (or even longer). Census errors often cancel out at higher levels of geography but for small areas they can be substantial, especially for some population subgroups (e.g., age, sex, and racial categories). Postcensal population estimates are subject to even larger errors than decennial census data. Data sources used for particular types of projections—such as birth and death statistics, IRS migration records, group quarters data, and employment forecasts—are also subject to error. It is essential to examine all input data, note potential errors, and make corrections or adjustments when possible. This is a time-consuming task, but can have a huge pay-off in terms of improving the quality of the projections.

How long a base period is needed? As noted in Chap. 13, there is little uniformity among practitioners. Choices vary according to projection method, length of projection horizon, and availability of historical data. For simple extrapolation methods only a few years of base data are needed for projections extending a few years into the future. Given the impact of reporting errors and random fluctuations in historical data series, however, we believe it is risky to use a single year of base data for *any* projection, even one covering a single year. For projections extending beyond 5 years, approximately 10 years of base data are needed to achieve the greatest possible forecast accuracy. Longer base periods can be used, but they will not necessarily raise forecast accuracy. One exception is EXPO projections for rapidly growing areas and SHIFT projections for rapidly growing or declining areas, where increasing the base period to 20 years seems to improve forecast accuracy by moderating the impact of extreme growth rates.

Very little research has considered this question for other projection methods. Some analysts believe at least 50 observations are necessary for applying time series methods (McCleary and Hay 1980) but this does not imply that 50 observations are needed to maximize forecast accuracy. In fact, some analysts have used as few as 11, apparently with reasonable results (Voss and Kale 1985). Cohort-component models often use the most recent data on migration and fertility rates, without attempting to account for changes over time. Many applications of structural and microsimulation models appear to use whatever data are available.

Other than for simple extrapolation methods, there are currently no general guidelines regarding how much base data should be used in constructing population projections. In making this decision the analyst must rely on his/her professional judgment, informed by theoretical considerations and empirical evidence. In some instances this decision will be determined primarily by the availability of relevant data.

14.2.4 Adjust for Special Events

It is important to adjust the base data for the effects of any special events that may have occurred. For example, large state prisons were built in several small Florida counties during the past decade. The populations of some of these previously slowly growing counties suddenly grew by 5, 10, or even 15% over a period of just a year or two. If projections were made using that decade as a base period and taking no account of these events, the analyst in essence would be projecting the construction of similar prisons during each future decade. This will generally not be a reasonable assumption. When this occurs, adjustments should be made by taking the special population out of the base data, making projections using the remaining data, and adding back a separate projection of the special population, as illustrated in Chap. 10.

Other types of special events may also have substantial, one-time-only effects on population growth. Examples include the opening or closing of a military base, college, or retirement home; the construction of a large housing development; and the addition or loss of a major employer. The effects of such events on population change are particularly great for areas with small populations. For areas with large populations, the effects of these types of events tend to cancel each other out and can usually be ignored.

Adjusting for special events requires intimate knowledge of the area to be projected. It also requires the application of professional judgment. Which events should be accounted for and which should be ignored? Should expectations of future events be considered or only events that have already occurred? Are there any spin-off effects of these events that might affect other aspects of population growth (e.g., what are the employment implications of building a new prison)? The analyst must answer these and similar questions before constructing the projections.

In addition to accounting for special events, the analyst must consider the potential effects of any constraints that may restrict future population growth. Constraints may be physical (e.g., swamps, lakes, flood plains) or political (e.g., zoning restrictions, land use plans, building moratoria). Such constraints are rarely important at the state level, but are often critical for county and especially subcounty areas. Some projection methods account for such constraints explicitly (e.g., urban systems models), but their impact should be considered when using other methods as well.

14.2.5 Control for Consistency

It is generally advisable to control small-area projections to projections of larger areas. For example, county projections might be controlled to state projections, or census tract projections controlled to county projections. Although there is no evidence that controlling improves forecast accuracy (Isserman 1977; Voss and Kale 1985), it does make small-area projections consistent with each other and with projections of larger areas. This will be particularly important when larger-area projections are "official" projections whose use is mandated by law or some other requirement. Controlling can be achieved using simple raking procedures or more complex approaches based on population change (see Chap. 10).

14.2.6 Account for Uncertainty

We can be pretty sure the sun will set tonight and rise again tomorrow morning. The earth has been rotating on its axis for a long time and the chances of that changing anytime soon are so slim that—for all practical purposes—we can accept its continuation as a certainty. Most future events, however, are subject to some degree of uncertainty. Will it rain tomorrow? Will the stock market go up or down next year? Will the Cubs ever win another World Series?

The course of future population change is also uncertain. The degree of uncertainty grows as the projection horizon becomes longer and as the size of the population becomes smaller. We can be much more confident of a 1-year forecast than a 20-year forecast. Similarly, we can be more certain of the future size of the U.S. population than the future size of the population living in Portland, Maine. The errors reported in Chap. 13 illustrate the uncertainty inherent in population forecasts.

We believe it is important to provide data users with some indication of uncertainty. This can be done in several ways. One is to construct a range of projections based on two or more methods or different specifications of a particular method. For example, projections might be made using several trend extrapolation methods and/or different base periods for each one. A more common approach is to produce several sets of cohort-component projections based on different combinations of assumptions. For example, fertility rates could be projected to rise by 10%, fall by 10%, or remain constant. Migration rates could be based on data from the last 2 years, 5 years, or 10 years.

The primary benefit of producing a range of projections is that it shows the populations stemming from different models, techniques, or sets of assumptions. The primary limitation is that it does not provide an explicit measure of uncertainty. How likely is it that the future population will fall within the range suggested by two alternative projections? How likely is it that any particular projection will provide an accurate forecast of future population change? These questions cannot be answered simply by producing a range.

An explicit measure of uncertainty can be given by constructing prediction intervals to accompany population forecasts (see Chap. 13). These intervals can be based on specific models of population growth or on empirical analyses of past forecast errors. Model-based intervals are difficult to produce and are subject to a variety of specification errors. Empirically-based intervals require the collection of a large amount of historical data. Both are valid only to the extent to which future error distributions are similar to past or simulated distributions. In spite of these problems, prediction intervals offer one major advantage over a range of projections: They provide an explicit measure of the uncertainty surrounding future population growth.

Forecast uncertainty can also be assessed by comparing more broadly defined projection scenarios. For example, scenarios can be based on alternative assumptions regarding land use patterns; the transportation system; and housing, economic, fiscal, and environmental policies. Under this approach, uncertainty is evaluated by considering various policy options; it is not intended to show a specific range of values or a precise numerical estimate for a particular area.

Another way to provide data users with some indication of uncertainty is to construct tables summarizing errors from previous forecasts for the area to be projected or for areas with similar characteristics. Although this approach does not provide an explicit range or prediction interval, it does provide an assessment of past performance and—by extension—a basis for predicting future performance.

Of course, it is important to remember that—as buried in the small print of mutual fund advertisements—past performance is no guarantee of future performance.

In some instances data users may be better off using a high or low projection rather than the forecast or "most likely" projection. For example, suppose that the cost to a city of building too large a sewer system is relatively small, but the cost of building too small a system is very large. To reduce risk it may be advisable to use a projection from the high series or at the high end of the prediction interval for planning the size of the system. Estimates of the cost of being wrong may play an important role in the choice of the projection to be used for any particular purpose. Measures of uncertainty help the data user make these choices.

Population projections used as forecasts are subject to error, especially for small areas, areas that have been growing or declining rapidly, and for long forecast horizons. These errors are caused by our inability to correctly predict the future course of mortality, fertility, and migration. We believe it is important to convey this information to the data user. Although it may be disappointing, information on potential errors will give data users a more realistic view of the future and help them plan more effectively for the uncertainty inherent in population projections.

14.3 Review and Document the Results

The analyst may believe the job is finished once the steps described above have been completed. That would be a mistake. At this point, the projections should be viewed as strictly preliminary. Before they are finalized they must be thoroughly reviewed and evaluated. Are the results plausible? Do they make sense given historical population trends in the area and projected trends in other areas? Are they consistent with the area's demographic characteristics and economic conditions? It is possible that there were flaws in the original projection methodology and assumptions, that errors were made in data entry or programming, or that something important was overlooked. A review and evaluation of the results will often uncover such problems. As the final step in the projection process, the entire methodology must be documented, describing all data sources, models, techniques, and assumptions.

14.3.1 Internal Review

By *internal review*, we mean an examination of the results by the person or agency producing the projections. This can be done in a variety of ways (Dion 2012; Murdock et al. 1991). We suggest several that we have found to be particularly helpful.

Suppose we are reviewing a set of county projections. It is useful to observe historical population trends and to compare past changes with projected changes.

Table 14.1 Average annual population change for Florida and selected counties, 1980–2010

Place	1980–1985	1985–1990	1990–1995	1995–2000	2000–2005	2005–2010
Broward	21,307	26,139	34,644	38,862	23,828	1,182
Duval	9,615	10,779	9,543	11,639	9,853	7,224
Marion	7,291	7,178	6,040	6,777	8,274	6,202
Pinellas	14,552	10,073	7,222	6,745	2,295	−3,286
Sumter	670	791	888	3,466	3,163	4,852
Union	87	−70	457	181	273	145
Florida	315,075	323,118	279,612	329,368	359,066	204,631

Source: Bureau of Economic and Business Research, University of Florida, unpublished data

Table 14.1 shows average annual population changes for Florida and several of its counties from 1980 to 2010. Duval and Marion exhibited fairly stable changes over the entire time period, albeit with a bit of a decline in 2005–2010 due to the severe economic recession near the end of the decade. Broward exhibited changes that increased steadily during the 1980s and 1990s but declined rapidly thereafter. Sumter exhibited changes that rose rapidly over time and Pinellas exhibited changes that declined rapidly, becoming negative for 2005–2010. Union exhibited substantial volatility over the entire time period.

Rapidly changing trends is a red flag warning the analyst to investigate the accuracy of the input data. If no errors are found, potential causes of the changes must be considered. There are logical explanations for several of the trends shown in Table 14.1. The volatility in Union County's population was caused by fluctuations in its large prison population. Increases in Sumter County's prison population contributed its growth in the late 1990s, but the main cause of the large population increase since 2000 was the development of a huge retirement community. Pinellas County is geographically small and densely populated; the steady decline in its population growth since 1980 was caused primarily by the growing scarcity of open space for further expansion. The severe recession in 2007–2009 slowed population growth almost everywhere in the state. Figuring out the causes of recent trends will help the analyst refine the methodology and perhaps revise the assumptions used in creating the projections.

Analyzing historical trends gives the analyst a basis for evaluating the plausibility of the projections. Are projected changes consistent with historical changes? If not, why not? If a logical explanation cannot be found, it may be a tip-off that an error was made in choosing the projection techniques, developing assumptions, or writing computer programs. Inspecting patterns of population change over the projection horizon also provides helpful clues. Do the projected changes become larger, smaller, or remain about the same as the horizon becomes longer? Is there a logical explanation for this pattern? If not, this is another red flag that must be investigated.

Similar tables could be constructed showing percent changes rather than numeric changes, or showing county population as a share of state population. These alternative forms provide different perspectives for viewing population change and judging plausibility. The specific form doesn't matter. What matters

Table 14.2 Percent distribution of the population by age for Florida, and selected counties, 1980–2010

Place	Age	1980	1990	2000	2010
Florida	<15	19.3	18.8	19.0	17.5
	15–44	41.8	43.3	40.7	38.2
	45–64	21.6	19.7	22.7	27.0
	65+	17.3	18.2	17.6	17.3
Alachua	<15	19.0	18.7	16.6	14.7
	15–44	60.5	57.6	54.5	51.6
	45–64	13.5	14.5	19.3	22.9
	65+	7.1	9.2	9.6	10.8
Seminole	<15	23.5	21.2	21.0	18.5
	15–44	46.2	49.5	44.7	41.5
	45–64	20.5	19.0	23.6	28.0
	65+	9.8	10.3	10.6	12.0
Sumter	<15	20.7	18.6	13.1	7.4
	15–44	40.0	36.9	32.2	20.3
	45–64	22.6	22.2	27.3	28.9
	65+	16.7	22.3	27.4	43.4

Source: Bureau of Economic and Business Research, University of Florida, unpublished data

is having a set of numbers that provides a basis for comparing projected changes with historical changes and for comparing changes in one area with changes in another.

It is also useful to construct summary tables for population characteristics such as age, sex, race, and ethnicity. Table 14.2 provides an example showing historical data for broad age groups for Florida and several of its counties. Several patterns stand out. One is the huge differences in age structure found among the three counties. Alachua County is the home of the University of Florida and has a very young population. Sumter County is a magnet for retirees and has a very old population (in fact, it had the highest proportion aged 65+ of any county in the United States in 2010). Seminole County falls in between, with an age structure similar to the nation as a whole. Not surprisingly, Florida's population is considerably older than the U.S. population.

Another pattern that stands out from this table is the aging of the population over time. The proportion less than age 15 declined more or less steadily between 1980 and 2010 for Florida and all three counties. The proportion aged 65+ remained fairly constant for the state as a whole but increased in the three counties, especially Sumter. The aging of the baby boom generation is also apparent. The proportion aged 15–44 declined steadily between 1990 and 2010 for Florida and all three counties and the proportion aged 45–64 increased. The continued aging of this generation will lead to large increases in the proportion aged 65+ over the next few decades.

Similar tables could be made showing the proportions female, black, Hispanic, and so forth. All would provide data for judging the plausibility of the projections. Are projected changes in demographic characteristics consistent with past changes? Are they consistent with previous and expected changes in birth rates, death rates, and migration patterns? Are the changes projected for one area consistent with those projected for another? If not, is there a logical explanation for the differences? Answers to these questions help the analyst evaluate the projections' plausibility and uncover any errors that may have been made.

Inspecting historical population changes and comparing them with projected changes is a tedious and time-consuming process; so too is comparing projections for one area with those for another. However, such an exercise is well worth the effort. It improves the analyst's understanding of the population dynamics of the areas being projected, uncovers data and computational errors, illustrates the consequences of questionable assumptions, and highlights the impact of factors such as special populations and growth constraints. Sometimes it points to the omission of factors that should have been included. We believe the internal review process is useful for projections at all levels of geography, but is particularly helpful for small areas because of their greater potential for error.

14.3.2 External Review

By *external review*, we mean an examination of the results by clients, public officials, advisory boards, and various groups of data users. In some circumstances there is no formal external review. Once the results have been reviewed internally, the process is complete. This is the case for general-purpose projections produced by the Census Bureau, by some state and local government agencies, and by most private data companies.

Even in these circumstances, however, projections may be subject to a great deal of *informal* external review. Data users often communicate their views (sometimes quite forcefully) regarding the projection methodology and results. These comments may refer to the validity of the data, techniques, and assumptions used in constructing the projections; to the level of geographic or demographic detail provided; or to the plausibility of the results. Feedback from data users sometimes has an impact on the production of future projections. For example, data producers may be persuaded to provide more demographic detail, to extend the projections further into the future, or even to revise the basic methodology.

In other circumstances a formal external review is a central part of the projection process (Tayman 1996, 2011). This is often the case for customized projections produced for a particular client or a particular purpose (e.g., local transportation planning). The client should always be given the opportunity to review and comment on the results before the projections are finalized; indeed, such an opportunity may be legally required. Given his/her knowledge of the projection area, the client may be able to spot irregularities the analyst missed. Those observations may lead to improvements in the quality of the projections.

A formal review gives the analyst a chance to describe the projection methodology to the client(s), explain why particular techniques and assumptions were used, and answer any questions that might arise. The review process itself may help the analyst convince the clients of the validity of the projections, which may be critical when the projections must have the clients' approval before they can be finalized. The review also gives the client an opportunity to make suggestions regarding the optimal format in which to display the projections. Of course, issues regarding geographic areas, age categories, projection horizons, and similar details should have been resolved before work on the projections was begun.

If the reviewers are dissatisfied with the results, the external review may be the most difficult part of the entire projection process. Dissatisfaction may be based on purely technical grounds, such as the choice of data sources, techniques, or assumptions. It is more likely, however, that dissatisfaction will be based on political and economic considerations. Population projections are used for distributing government funds, allocating various types of permits, regulating the expansion of businesses, and planning the development of infrastructure and public facilities. They may even determine the salaries of public officials and the winners and losers in high-stakes games allocating political power and economic resources. It is no wonder that population projections are sometimes so controversial.

In some circumstances external reviewers play only an advisory role; in other circumstances they have the power to require that changes be made. This may put the analyst in a precarious position, attempting to balance technical competency with political expediency. At its best an external review presents new insights, provides a final opportunity to catch errors, and promotes public support and acceptance. At its worst it destroys the integrity of the process and the credibility of the projections. The successful analyst may have to be as skilled in the arts of political persuasion and negotiation as in the technical aspects of population forecasting.

14.3.3 Documentation

A complete written description of the projection methodology should accompany the projections. This report should cover data sources, projection methods, assumptions, special adjustments, and any other factors considered in constructing the projections. The reasons for choosing the forecast or "most likely" projection should be spelled out clearly. It is also helpful to discuss the range of projections, including the expected degree of forecast accuracy of the "most likely" projection, given its past performance or some other measure of uncertainty. A comparison of projected trends with past trends and with projections in other areas provides a context for considering the implications of the projections.

The methodological description should be comprehensive but clear, covering all aspects of the projection process in terms that can be understood by the data user. Balancing completeness and clarity can be tricky. It is sometimes helpful to put the most technical material in an appendix or a separate report. Alternatively, a general description of the methodology and results can be put in an executive summary, with the detailed description in the main body of the report. A clear description of the methodology helps data users understand and evaluate the projections and decide how they might best be used. For some data users the projections will be worthless without a description that is detailed enough to allow the results to be replicated.

Writing up the methodological description also helps the analyst review the entire projection process and note any parts requiring further consideration. Are some data sources of dubious quality? Are some assumptions particularly questionable? Have all the relevant factors been taken into account? What improvements might be made next time around? Documenting all the steps in the projection process helps the analyst uncover weak spots in the methodology and develop a strategy for dealing with them.

Thorough documentation is also essential for replicating the projections at a later date. It is much easier to repeat or revise a methodology used successfully in the past than to create a new one from scratch. Written documentation is particularly important when staff turnover takes away the analyst(s) with direct knowledge of the methodological details of an earlier set of projections. New staff members will be extremely grateful for a clear, comprehensive description of the projection methodology used previously.

14.4 Conclusions

The guidelines presented in this chapter will not answer every question and solve every problem that might be encountered when making small-area population projections. Every set of circumstances is unique in one way or another, with special factors that must be considered before reasonable projections can be made. Consequently, every set of projections is unique. However, there are many commonalities shared by virtually all small-area projections; these commonalities provide a basis for developing a general set of guidelines.

Following these guidelines will not guarantee the accuracy of population forecasts, of course. Even the most brilliant analyst—armed with high-quality data, sophisticated models, and extensive knowledge of the area—may produce a forecast that turns out to be wildly inaccurate. There are no crystal balls, no magic potions, and no guarantees, but we believe these guidelines can help the analyst focus on the relevant issues, make reasonable choices, and avoid common mistakes. These are modest accomplishments, perhaps, but at least they provide some degree of comfort in a world of high pressure, high stakes, and limited resources.

Seldom—if ever—does an analyst have unlimited resources when constructing a set of population projections. Consequently, trade-offs have to be made. More time spent on one phase of the projection process (e.g., data collection) typically implies less time available for another phase (e.g., developing a methodology). Greater geographic coverage typically reduces the amount of demographic detail that can be included. A common objective in the field of applied demography is to do what is necessary to support practical decision making while minimizing time and money costs (Swanson et al. 1996). We believe the guidelines discussed in this chapter will help the analyst focus on the relevant issues and make the trade-offs needed to produce the best possible projections for the lowest possible cost.

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Epilogue: Some Final Thoughts

Using the past to project the future has been likened to driving a car by looking in the rear view mirror (Beck 1996). There is certainly some truth in this analogy. All the projection methods discussed in this book were based—in one way or another—on the extrapolation of past trends. But what is the alternative? If the windshield is covered with mud but the back window is clear, what offers the greater chance for keeping the car on the road (or at least on the shoulder): staring into the blank windshield in front of us or drawing inferences from the curves, hills, and potholes in the road behind us?

In reality, all objective projection methods—including cohort-component, structural, and microsimulation models as well as simple trend extrapolation techniques—are based on historical observations. Likewise, subjective projections based on intuition, experience, or expert judgment are distilled from the analyst's knowledge and understanding of past experiences. Only visions of the future inspired by dreams, tea leaves, or the stars may be truly free of the past. Even for these, who knows what part of a vision was actually inspired by historical events? As Keyfitz (1982) noted, pending the discovery of a truly behavioral way of projecting the future, we cannot afford to be ashamed of extrapolating the regularities observed in the past.

How can the extrapolation of past regularities be improved? Population projection methods differ primarily with respect to the time frames they cover, the variables they include, the ways in which those variables are related to each other, and their assumptions regarding future changes in variables and their interrelationships. Future changes in the field of population projections will therefore stem from changes in the availability of data, the development of new tools for organizing and manipulating data, new insights regarding the determinants of population change, and the development of new models or methods based on these new insights. The inspired analyst will incorporate factors not previously considered or will put them together in creative new ways. That inspiration, however, will still be firmly rooted in the past.

What recent developments might change the way population projections are made? Are any new methods or data sources being investigated? Will changes in computing capabilities and geographic information systems have an impact? Are any "paradigm shifts" imminent?

S.K. Smith et al., *A Practitioner's Guide to State and Local Population Projections*,

The Springer Series on Demographic Methods and Population Analysis 37,
DOI 10.1007/978-94-007-7551-0,

Paradigm shift (Source: Thaves 1989 (reprinted with permission))

The availability of mortality, fertility, and migration data has evolved over the years. We don't anticipate any major changes in the availability or quality of mortality and fertility data in the foreseeable future, but important changes in migration data are already occurring. Annual migration estimates based on IRS records became available during the late 1970s. Not only were these data more timely than migration data from the decennial census, but they made it possible to apply projection methods based on annual data series (e.g., ARIMA time series models).

Even more important has been the loss of the census long from and its replacement by the American Community Survey (ACS). ACS migration data are based on a smaller sample size than long-form migration data, refer to a 1-year rather than a 5-year migration interval, and are available annually rather than once per decade. In addition, the Census Bureau will be releasing fewer detailed migration tables for the ACS than it did for the decennial census (see Chap. 6). These differences will have a major impact on the way cohort-component projections are made, especially for small areas. In particular, we believe net migration models (including the Hamilton-Perry method) will be used more frequently than in the past; gross migration models will be used less frequently; when gross migration models are used, they will often be based on synthetic data series drawn from several data sources such as the ACS, the Current Population Survey, and the IRS records; and models based on single-year age groups and migration intervals will become more common.

Population projections are often based on population estimates. These estimates are typically derived from symptomatic indicators of population change such as births, deaths, tax records, building permits, electric customers, school enrollment, and Medicare enrollees. Changes in information technology will increase the number and variety of data series that might be used as symptomatic indicators, and will make them more readily available to a larger number of data users. In addition, the expansion of geographic information systems will make it possible to tabulate these data at lower and lower levels of geography. These changes will have an important (albeit indirect) impact on population projections, especially for very small areas.

The utilization of data at smaller and smaller levels of geography (all the way down to the individual parcel, household, or person) would not be possible without the tremendous improvements in computing capabilities that have occurred over the years. We see no reason why further improvements will not continue to be made. Combined with the appearance of new types of data, we expect that advances in computing capabilities will lead to projections covering increasingly detailed socioeconomic and demographic characteristics at ever smaller units of geography.

Of particular importance in this regard is the emergence of "Big Data." This term refers to the huge amount of digital data that have become available in recent years from an ever-expanding number of sources. It includes both structured and unstructured data and is characterized by massive volume, velocity (i.e., frequency), and variety (Dijcks 2012). It encompasses traditional administrative records from government agencies as well as a vast array of business transactions, e-mail messages, web searches, social media postings, spatial movements, photos, and surveillance videos. The emergence of Big Data was facilitated by the development of new software systems and the ability to store tremendous amounts of data in the cloud. We believe it will lead to new approaches to making population estimates and projections.

We don't know exactly what these new approaches will be, but we expect them to be innovative and extremely useful. For example, the location-tracking capabilities of cell phones may facilitate the development of estimates of temporary population movements such as commuting and seasonal migration. These estimates of temporary movements could be combined with estimates of permanent residents to construct estimates of the de facto population; projections based on historical trends in that population could also be developed. De facto-based estimates and projections would be invaluable for a wide variety of planning purposes in both the public and private sectors (e.g., emergency management, infrastructure needs, and the demand for various types of goods and services). Big Data may indeed herald a paradigm shift, not only in demography but in other fields as well.

We believe the data and methods used in constructing population projections will continue to evolve, both along the lines suggested in this book and in ways not yet imagined. There will be changes in the ways we think about the future (Romaniuc 2003, 2010) and in our perceptions of how the past shapes the future (Mead 1932). Despite these changes, we cannot escape the fact that the future is uncertain. Donald Rumsfeld, Secretary of Defense in the George W. Bush administration, famously warned about unknown "unknowns," those things we don't know that we do not know (U.S. Department of Defense 2002). Nassim Taleb, essayist and scholar, warned of "Black Swans," those rare events that have an extreme impact but are essentially unpredictable (Taleb 2007). As we strive to improve the accuracy, scope, and overall usefulness of population projections—and achieve some successes along the way—the essential uncertainty of the future will keep us humble as forecasters. As noted in Chap. 13, providing a clear warning about forecast uncertainty may be the most useful service the producers of population projections can provide to the users of their projections.

The widespread availability of data and software will make it possible for more and more people to make population projections and to make them faster, cheaper, and with greater detail than ever before. The Internet- and cloud-based services will allow unprecedented access to projections at home, work, and on the road. These trends will be generally beneficial for data users and will raise the overall usefulness of population projections. However, it will also lead to more projections based on ill-founded assumptions, inadequate attention to detail, vested political or economic interests, and a poor understanding of the causes of population growth and demographic change. Data users will face a broader array of options than ever before and will have to do their homework in order to make the best possible decisions. We hope this book will help them as they go through that decision-making process.

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Glossary

Administrative records Records kept by agencies of federal, state, and local governments for purposes of registration, licensing, and program administration. These records provide information on demographic events and population changes and are frequently used for constructing population estimates.

Age structure (see **Population composition**)

Age-specific rate A statistical measure that relates the number of demographic events (e.g., births, deaths) for a specific age group to the corresponding at-risk population. Age-specific rates are typically calculated by dividing the annual number of events by the midyear population in each age group.

American Community Survey (ACS) A monthly household survey conducted by the Census Bureau designed to provide socioeconomic and demographic information for states, counties, and a variety of subcounty areas. The ACS covers approximately 250,000 households each month and has replaced the long form of the decennial census.

At-risk population The set of people to whom a demographic event (e.g., birth, death, and migration) might potentially occur. Ideally, the at-risk population is measured by the total person-years lived during the relevant time interval. In practice, it is often approximated by the midyear population.

Autoregression Integrated Moving Average (ARIMA) model A model that bases projections of future values in a time series on the patterns of change in its historical values. Historical values are typically expressed as differences and future values are expressed as a function of previous values and previous errors.

Base year The year of the earliest data used to make a projection.

Big data Digital data characterized by massive volume, velocity (i.e., frequency), and variety. It encompasses traditional administrative records as well as a vast array of business transactions, email messages, web searches, social media postings, spatial movements, photos, and surveillance videos.

Block group A cluster of blocks, typically containing between 250 and 550 housing units at the time of a decennial census.

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Block A small geographic area bounded on all sides by identifiable features (e.g., roads, rivers, property lines, city limits). A block is the lowest geographic level for which decennial census data are tabulated.

Bottom-up model In a hierarchically nested geographic system, a model in which an estimate or projection for a higher-level geographic unit (e.g., a state) is computed by summing the estimates or projections for lower-level geographic units (e.g., counties).

Census survival rate A measure of survival from one census year to another. For censuses conducted every 10 years, it is calculated by dividing the population age $t + 10$ in one census by the population age t previous census. Also called a *cohort-change ratio*, this measure includes the effects of mortality, migration, and census enumeration errors.

Census tract A small, relatively permanent statistical subdivision of a county. Census tracts are designed to be homogenous with respect to population and socioeconomic characteristics and typically contain between 2,500 and 8,000 persons at the time of a decennial census. Although census tract boundaries are intended to remain constant over time, changes reflecting population growth or decline often occur.

Census A count of the entire population of a specific geographic area at a specific time. The U.S. government has conducted a census every l0 years since 1790; that is, the United States has a *decennial* census. The Census Bureau and state and local governments occasionally conduct special censuses for particular cities, counties, and other small areas for years between decennial censuses.

Child-woman ratio The number of children (e.g., aged 0–4) divided by number of women of childbearing age (e.g., aged 15–44) at a given point in time.

Closed population A population in which there is no migration and population growth is determined solely by births and deaths. For example, the population of the world as a whole is "closed," whereas the population of New York City is not.

Cohort A group of people who experience the same significant event during a particular time interval. For example, all persons married in 2013 are the marriage cohort for that year and all persons born during the 1990s are the birth cohort for that decade.

Cohort perspective A longitudinal view of demographic events and other life experiences for a particular cohort as it progresses through time.

Cohort-change ratio (see **Census survival rate**)

Cohort-component method A method in which the components of population change are projected separately for each age-sex group in a population.

Components of population change The demographic events that determine population change: births, deaths, and migration. A population grows through the addition of births and in-migrants and declines through the subtraction of deaths and out-migrants.

Controlling The process of adjusting a geographic or demographic distribution to an independently derived total. For example, county population projections can be controlled to an independent state projection and age groups from one projection can be controlled to the total population from another projection. *Raking* is a synonym.

Core-Based Statistical Area (CBSA) A geographic area defined by the U.S. Office of Management and Budget based around an urban center of at least 10,000 people and adjacent areas that are socioeconomically tied to the urban center by commuting. CBSAs include both metropolitan areas (urban centers with at least 50,000 residents) and micropolitan areas (urban centers within between 10,000 and 50,000 residents).

Crude rate A statistical measure in which the number of demographic events during a time interval is divided by the total population. For example, the crude birth rate is the annual number of births divided by the midyear population.

Current Population Survey (CPS) A sample survey of approximately 60,000 U.S. households conducted monthly by the Census Bureau. The survey collects data covering a wide range of social, economic, and demographic characteristics. Some characteristics are available annually for states and large metropolitan areas, but many are available only at the national and regional levels.

Curve fitting The process of finding the mathematical formula that describes a particular data set (typically measured over time).

De facto population A census concept that defines an enumerated person on the basis of his or her actual location at the time of the census.

De jure population A census concept that defines an enumerated person on a basis other than his or her actual location at the time of the census. The most common basis is the person's place of usual residence, typically defined as the place the person lives and sleeps more than any other place.

Demographic balancing equation A demographic formula in which population change is expressed as births minus deaths plus in-migrants minus out-migrants. An error term is sometimes included to account for measurement errors.

Domestic migration (see **Internal Migration**)

Econometric model An equation (or set of equations) in which the relationships between independent and dependent variables are estimated using statistical methods. For population projections, independent variables are typically economic variables and dependent variables are demographic variables.

Emigration (see **International migration**)

Error of closure A term added to the demographic balancing equation to account for errors in population counts (or estimates) and errors in the measurement of the components of population change.

Estimate A calculation of a current or past value of a variable (e.g., population). Estimates are often based on symptomatic indicators of change in the variable's values, but can also be based on extrapolation or interpolation methods.

Extrapolation The process of using mathematical formulas or graphical procedures to determine values that fall beyond the last known value in a series of numbers.

Face validity The extent to which a projection uses the best methods for a particular purpose, is based on reliable data and reasonable assumptions, and accounts for the effects of relevant factors.

Forecast The projection selected as the one most likely to provide an accurate prediction of the future value of a variable (e.g., population).

Forecast error The difference between forecasted and actual (or estimated) values of a variable. The magnitude of the difference—measured in either numeric or percent terms—is called *accuracy* and the direction of the difference is called *bias*.

Foreign migration (see **International migration**)

General fertility rate The number of births during a time interval (e.g., a year) divided by the number of women of childbearing age (e.g., 15–44). *Fertility rate* is a synonym.

Geocoding The assignment of a specific geographic location (e.g., latitude and longitude) to a person, household, or other entity. These locations are often based on information regarding addresses, intersections, or other clearly recognized landmarks.

Geographic Information System (GIS) A chain of operations involving the collection, storage, analysis, and manipulation of data referenced by geographic or spatial coordinates.

Gravity model A model based on the assumption that the movement of people between two geographic areas (e.g., migration or commuting) is directly related to the size of their populations and inversely related to the distance between the two areas.

Gross migration The movement of migrants into or out of an area.

Hamilton-Perry method An abbreviated cohort-component method in which projections of population change are based on cohort-change ratios.

Immigration (see **International migration**)

Internal (or domestic) migration Migration from one place to another within the same country. People who enter an area are called in-migrants and people who leave are called out-migrants.

International (or foreign) migration Migration from one country to another. People entering a country are called immigrants and people leaving a country are called emigrants.

Interpolation The process of using mathematical formulas, graphic procedures, and/or values from a related data series to calculate intermediate values that fall between two known values.

Labor force The sum of the employed (full-time or part-time) and unemployed (without a job but actively seeking work) populations at a given point in time.

Labor force participation rate The proportion of the population in the labor force. The labor force participation rate is typically calculated by dividing the labor force population by the total adult population (e.g., age 16 and older). Rates can also be calculated for specific subgroups of the population (e.g., age, sex, race).

Launch year The year of the most recent data used to make a projection.

Life expectancy The average number of years of life remaining to people who reach a given age, assuming the continuation of a particular set of age-specific survival rates.

Life table survival rate A statistical measure that shows the probability of surviving from one exact age (or age group) to another, given a particular set of age-specific death rates.

Life table A statistical table showing measures of mortality, survival, and life expectancy for each age group in the population. *Period* life tables use mortality and age data from a single point in time, whereas *cohort* life tables use data for a particular birth cohort as it ages over time. *Complete* life tables contain information by single year of age, whereas *abridged* life contain information for broader age groups (e.g., 5 or 10 years).

Long form The decennial census questionnaire given to a sample of households (approximately one in six) in every U.S. census between 1940 and 2000. This questionnaire collected information on a wide range of socioeconomic, demographic, and housing characteristics. The long form was discontinued after the 2000 census and has been replaced by the American Community Survey (ACS).

Master Address File (MAF) A set of records maintained by the Census Bureau that attempts to contain the address of every housing unit in the United States. The MAF forms the basis of the decennial census, the ACS, and a number of other surveys.

Metropolitan area A geographic area represented by a large population nucleus and adjacent communities that have a high degree of economic and social integration with the nucleus. A metropolitan area consists of one or more counties and must contain either a place with a minimum population of 50,000 or a Census Bureau-defined urban area with a total population of at least 100,000.

Microsimulation models Models that operate at the level of individual units (persons, households, firms), with each unit represented by set of associated attributes.

Migrant A person who changes his or her place of usual residence from one political or administrative area to another.

Migration interval The period of time over which migration is measured.

Migration The process of changing place of usual residence from one political or administrative area to another.

Mobility The process of changing place of usual residence from one address (e.g., house or apartment) to another. The move can be as short as across the street or as long as across the country or around the world.

Model schedule A set of age-specific demographic rates (birth, death, migration) based on mathematical models summarizing the empirical regularities found in many populations. Different schedules can be identified for populations with differing characteristics. Model schedules can be used for estimates and projections of populations for which detailed demographic data are missing or unreliable.

Mover A person who changes his or her place of usual residence from one address (e.g., house or apartment) to another.

Multiregional model A model in which migration is represented by origin–destination-specific gross migration flows. For example, a multiregional model may contain a 51 $\times$ 51 matrix depicting migration between each pair of states and the District of Columbia.

Natural increase (decrease) The excess of births (deaths) over deaths (births).

Net migration The difference between the number of in-migrants and the number of out-migrants.

Nonrecursive model A structural model that accounts for two-way interactions between independent and dependent variables. For example, the model may account for the effect of wage rates on migration and the effect of migration on wage rates.

Period perspective A cross-sectional view of demographic events and other life experiences in which the combined events and experiences of all cohorts are measured at a given point in time.

Person-years lived The total number of years lived by a population during a given time interval (e.g., 5 years). It is calculated by adding up the exact number of years (or fractions thereof) lived by each member of the population during the interval.

Place of residence According to Census Bureau guidelines, this is the place where a person lives and sleeps more than any other place. It is sometimes called the place of *usual* or *permanent* residence.

Plausibility The extent to which a projection is consistent with historical trends, with the assumptions inherent in the model, and with projections for other areas.

Population composition The classification of members of a population according to one or more characteristics such as age, sex, race, ethnicity, income, and educational attainment.

Population distribution The spatial spread of a population among geographic areas such as states, counties, census tracts, and parcels.

Prediction interval An estimate of the probability that a given range of projections will encompass the actual future value of the variable (e.g., population). Prediction intervals can be based on past forecast errors, statistical models, expert judgment, or a combination of these approaches.

Projection horizon The interval between the launch year and target year of a projection.

Projection interval The increments in which projections are made. For population projections, 1- and 5-year intervals are the most common.

Projection The numerical outcome of a particular set of assumptions regarding future values of a variable (e.g., population).

Public Use Microdata Sample (PUMS) A small sample of responses selected from the decennial census or a survey such as the American Community Survey. PUMS data sets provide population, housing, and socioeconomic information for individual respondents but are available only for places with a large number of residents (e.g., 100,000 or more).

Raking (see Controlling)

Recursive model A structural model that accounts only for one-way interactions between independent and dependent variables. For example, the model may account for the effect of wage rates on migration, but not the effect of migration on wage rates.

Sex ratio The number of males per 100 females.

Short form The decennial census questionnaire collecting information on a limited number of demographic and housing characteristics. Between 1940 and 2000, the short-form went to approximately five in six households in the United States. In 2010, it went to all households.

Special population A group of persons who reside in an area because of an administrative or legislative action. Common types include prison inmates, residents of nursing homes and college dormitories, and military personnel and their dependents.

Structural model A statistical model that relates changes in population (or one of its components) to changes in one or more variables (e.g., employment, income, land use, and the transportation system).

Survival rate (see **Census survival rate**; **Life table survival rate**)

Synthetic population A data base containing the hypothetical or synthetic characteristics of each individual unit (e.g., person, household). These characteristics are derived from the distribution of population characteristics in small geographies (e.g., census tracts, block groups, or blocks) and are used in microsimulation models.

Synthetic projections Projections of demographic rates for one population that are based on the changes in those rates projected for another population. For example, age-specific death rates for a state could be projected to change at the same rate as age-specific death rates for the United States.

Synthetic rates Demographic rates based on data from several different sources. For example, age-sex-race-specific death rates for a county could be based on the corresponding state-level rates or migration rates for males could be based on rates for females in places with a large male-only prison. Synthetic rates are similar to rates from model schedules but can be based on a broader variety of data sources and estimation techniques.

Target year The year for which a variable is projected.

Time series An ordered sequence in which the values of a variable are measured at equally spaced time intervals.

Top-down model In a hierarchically nested geographic system, a model in which projections for a lower geographic level (e.g., counties) are adjusted so that they add to a projection for a higher geographic level (e.g., a state).

Topological Integrated Geographic Encoding and Referencing System (TIGER) A digital database developed by the Census Bureau in which residential addresses, physical features (e.g., streets, rivers), political boundaries (e.g., cities, counties), and census statistical boundaries are assigned exact spatial locations.

Total fertility rate The average number of children that a group of woman would have during their lifetimes if none died and their fertility behavior conformed to a given set of age-specific birth rates.

Traffic Analysis Zone (TAZ) A small geographic area designed for purposes of transportation modeling and planning. A TAZ is usually smaller than a census tract.

Trend extrapolation method A projection method in which projected values of a variable are based solely on its historical values.

Vital statistics Data that reflect the registration of vital events such as births, deaths, marriages, divorces, and abortions.

ZIP code area A postal delivery area delineated by the U.S. Postal Service. Although ZIP code areas do not always correspond to census geographic boundaries, they are widely used for small-area demographic analyses.

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