Lecture Notes in Mobility

Akimasa Fujiwara
Junyi Zhang *Editors*

Sustainable Transport Studies in Asia

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Sustainable Transport Studies in Asia

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Preface

Sustainable Transport Studies in Asia

Various studies of sustainable transport in Asia have been carried out and various so-called successful policies have been implemented. However, common transportation issues (e.g., traffic congestion, traffic accidents, and air pollution) can still be observed here and there, not only in developing countries but also in developed ones. Solving some of the issues is just a matter of time and/or money. Unfortunately, many of the other issues have not been well examined before policies were implemented, or have not even been well understood. Even for those "matter of time and/or money" issues, the nature of the problems might dramatically change as time passes, which sometimes makes problem solving much more difficult. Motivated by the existence of the above widely observed troublesome issues, the authors' research team members conducted joint interdisciplinary research with the support of several sources of funds, including:

1. The 21st Century Center of Excellence (COE) Program "Social Capacity Development for Environmental Management and International Development," Japan Society for the Promotion of Science (2003–2008)
2. The Global Environmental Leaders Education Program for Designing a Low-Carbon World, MEXT Special Coordination Funds for Promotion of Science and Technology (2008–2012)
3. Development of Cross-Sector Urban Planning and Management Methodologies by Establishing Theory of Citizens' Life Decisions and Behavior, Grants-in-Aid for Scientific Research (A), JSPS (Japan Society for the Promotion of Science) (2010–2014; No. 22246068).

This book, consisting of 11 chapters, collects some of our research findings on sustainable transport in Asia. Chapter 1 quantitatively explores the issues of sustainable transport development in cities at different developmental stages in the world based on longitudinal survey data. Chapter 2 argues the importance of systematic and behavioral methodologies in decisions on transport policies and illustrates major methods and future challenges. Chapter 3 develops a four-step transport demand model with full feedback mechanisms and applies it to the exploration of environmentally sustainable urban forms in Beijing, China, and the Jabodetabek Metropolitan Area (JMA), Indonesia, based on data from full-scale person trip surveys. Different from Chapter 3, which is based on a bottom-up approach, Chapter 4 deals with a hybrid approach, which combines top-down and bottom-up approaches, to identify policies that meet sustainable transportation development goals. Looking at interregional transportation issues, Chapter 5 examines how interregional transportation policies influence tourism demand from the perspective of transportation networks. Focusing on "paratransit", the most popular travel mode in many developing countries, Chapter 6 reveals how people in a developing megacity (Jakarta, Indonesia) adapt their travel behavior and lives to the paratransit-oriented transportation system, where social sustainability is especially emphasized from the points of view of both supply and demand. Environmental sustainability is critical to the realization of a sustainable transport society. In line with this consideration, Chapter 7 explores several major behavioral issues related to sustainable tourism in an integrated way, Chapter 8 discusses how ownership and use of environmentally friendly passenger cars can be promoted especially by targeting the role of taxation policies, and Chapter 9 deals with household energy consumption behavior across residential and transport sectors. The role of technological innovation in transport policy is addressed in the context of traffic safety in Chapter 10, focusing on intelligent transportation systems (ITS) technologies and behavioral changes. Finally, Chapter 11 mainly illustrates how to deal with various uncertainties in travel behavior analysis, which is, in fact, also useful to more general transportation studies.

These 11 chapters examine a variety of sustainable transportation policies in Asia in a comprehensive way based on diverse, scientifically sophisticated methodologies. Policies cover "avoid/reduce" policies (urban form, comprehensive transportation network, control of car ownership and use, and integrated tourism development), "shift/maintain" policies (public transportation network improvement, paratransit-adaptive transport system, modal shift in interregional tourism), and "improve" policies (low-emission vehicles, ITS and safety, sustainable mobility, and cross-sectoral household energy policies), in line with the famous Avoid–Shift–Improve framework. Cross-sectoral policies are further emphasized from the perspectives of land use and transportation systems, tourism and transportation, and household energy consumption in domestic and transport sectors. To examine these policies, both systematic and behavioral methodologies are adopted. Systematic methods include an improved four-step travel demand model with full feedback mechanisms and a bi-level programming model with sustainability goals. Modeling techniques for behavioral studies include discrete and/or continuous choice models, multilevel models, copula models, frontier analysis approaches, structural equation models with latent variables, and driving risk models with short-term memory, among others. How to deal with uncertainties is also described. Case studies are conducted in megacities and local cities of Japan, China, and Indonesia. In the above analyses, a series of pathways to sustainable transport in diversified Asia are explored.

Readers will find state-of-the-art methodologies and learn about their context-responsive applications throughout the book. Our greatest hopes will be fulfilled if the book can be helpful to policy decision makers, professional designers and operators, and academic and practical researchers in the field of transport planning around the world.

Finally, we would like to express our sincere gratitude to the following persons and institutes for their valuable advices and support: Prof. Md. Jobair Bin Alam (Bangladesh University of Engineering & Technology), Prof. Kay W. Axhausen (ETH Zurich, Switzerland), Prof. Haruo Ishida (University of Tsukuba, Japan), Prof. Atsushi Fukuda (Nihon University, Japan), Dr. Jifu Guo (Director, Beijing Transportation Research Center, China), Prof. Tetsuro Hyodo (Tokyo University of Marine Science and Technology, Japan), Dr. Backjin Lee (Korea Research Institute for Human Settlements), Prof. Takayuki Morikawa (Nagoya University, Japan), Assoc. Prof. Yasunori Muromachi (Tokyo Institute of Technology, Japan), Prof. Moon Namgung (Wonkwang University, Korea), Prof. Emeritus Katsutoshi Ota (The University of Tokyo, Japan), Dr. Lee Schipper (deceased: University of California Berkeley and Stanford University, USA), Assoc. Prof. Metin Senbil (Gazi University, Turkey), Prof. Chunfu Shao (Beijing Jiaotong University, China), Dr. Hiroshi Shimamoto (Kyoto University, Japan), Prof. Mamoru Taniguchi (University of Tsukuba, Japan), Prof. H.J.P. Timmermans (Eindhoven University of Technology, The Netherlands), Prof. Zhongzhen Yang (Dalian Maritime University, China), Prof. Toshiyuki Yamamoto (Nagoya University, Japan), Prof. Lei Yu (Texas Southern University, USA), Chogoku Regional Branch, West Nippon Expressway Company Limited and Technical Research Center, Mazda Motor Corporation, Japan as well as many of the graduates from the Transport Studies Group of Hiroshima University, Japan.

Hiroshima, Japan

Akimasa Fujiwara
Junyi Zhang

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Chapter 1
Evaluating Sustainability of Urban Development in Asia

Akimasa Fujiwara

Abstract To realize a sustainable urban society, policy makers and other stakeholders are required to make efforts to improve governance, which requires informative indicators. In line with this consideration, in this study, we first provide a systematic overview of existing indicators of sustainable development. Then we establish a dynamic structural equation model (SEM) to capture complex cause–effect relationships and state dependence in urban sustainability indicators. Furthermore, to resolve the conflict between economic and environmental sustainability, we propose an environmental efficiency (EE) model that expands the concept of the data envelopment analysis (DEA) cost-efficiency model. The SEM analysis is based on a longitudinal survey data collected from 46 cities in developed and developing countries in the years of 1960, 1970, 1980 and 1990. It reveals that energy consumption was mainly determined by previous energy consumption behavior and transport supply policies, and that the influence of land use is very limited in the dynamic context. Finally, it is confirmed that the EE model is a useful tool for the establishment of more plausible targets for energy-saving policies.

Keywords Data envelopment analysis • Dynamic analysis • Environmental efficiency • Sustainability indicators

1.1 Introduction

Developing countries face unprecedented challenges in achieving sustainable societies in the sense that they must balance economic growth and environmental considerations although they are not major contributors to environmental burdens.

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There are numerous constraints on societal development. Such constraints result from the laws of nature, physical environments (e.g., available space, waste absorption capacity of soils, rivers, oceans, the atmosphere, availability of renewable and nonrenewable resources), solar energy flow and material resource stocks, carrying capacity, human actors, organizations and cultures, technology, ethics and values, and so on (Bossel 1999). These constraints reduce the total range of future possibilities and consequently leave only a limited, potentially accessible set of options (i.e., accessibility space). Unlike the circumstances during the early stages of development of the developed countries, developing countries must pay increasing attention to this accessibility space to realize the same level of economic growth.

Various definitions of sustainable development have been proposed. One of the most commonly cited definitions emphasizes the economic aspects of sustainable development: "economic development that meets the needs of the present generation without compromising the ability of future generations to meet their own needs" (World Commission on Environment and Development 1987). However, sustainable development of human society also has environmental, material, ecological, social, legal, cultural, political and psychological dimensions that require attention (Bossel 1999). Currently, sustainability in global development is regarded as an explicit goal, but the concept must be translated into practice in the real world to make it operational. In this sense, it is becoming increasingly important to realize sustainable development in urban environments, where a growing proportion of people reside. Presently, the importance of sustainability of urban development is widely recognized by not only environmentalists, but also firms and governmental bodies (Newman 1999).

Various factors such as land use, travel behavior patterns, transportation networks, energy consumption patterns, technological progress, education levels and residents' environmental attitudes may influence the sustainability of urban development. These factors interact, show temporally changing cause–effect relationships and exert varying degrees of influence over sustainability at different stages of urban development. In this sense, sustainability is a dynamic concept. To evaluate sustainability, it is therefore necessary to develop comprehensive evaluation models that explicitly incorporate interactions among these factors across space and over time. For example, integrated land-use and transportation models (review refers to, for example, Timmermans 2003; Miller 2006) could play such role. However, such models with spatial interactions require spatial (zonal or mesh-type) data, which usually is not available, or is difficult to gather, in developing countries. Accordingly, researchers are urged to develop simplified evaluation models with data availability in mind. Such simplified models could provide practical indicators for policy makers. As Segnestam (2002) has pointed out, indicators have long been used as a tool to gather information about issues as varied as people's health, weather, and economic welfare. Indicators provide information on matters of wider significance than those that are actually measured or perceptible and trends or phenomena that are not immediately detectable (Hammond et al. 1995). Of course, indicators are not an end in themselves—they are the means to an end, which is improved decision making. To take a step closer to that end, analyses based on indicators are required. These analyses provide information, which is the basis for sound decision making (Segnestam 2002).

Compared with indicators of economic and social aspects, environmental and sustainable development indicators are a relatively new phenomenon. The Rio Conference on Environment and Development in 1992, and similar environmental milestone activities and events, recognized the need to improve the quality and quantity of knowledge and information about environmental conditions, trends, and impacts. In recent years, considerable work has been performed on environmental and sustainable development indicators at both national and international levels (Niemeijer 2002). The geographic focus of these reports varies from regional (e.g., Jones et al. 1998) to national (e.g., The Heinz Center 1999) to multinational (e.g., World Economic Forum 2001). Their focus ranges from a particular sector such as transport (e.g., EEA 2000) or agriculture (e.g., MAFF 2000) to the environment in its broadest sense (e.g., EEA 2001) by examining indicators of sustainable development (e.g., IWG-SDI 2001). Reports further vary in whether they consider only the state of the environment (e.g., NRC 2000) or also examine driving forces, pressures and responses (e.g., OECD 2001). Therefore, to understand better the general picture of urban sustainability, the first half of this chapter attempts to provide some practical indicators of urban sustainable development to support policy decisions, considering the availability of data in developing countries.

In addition, public concern about environmental issues is currently growing. The transport sector is no exception, and the heated debate and serious negotiations over countermeasures have been conducted at national and city levels. Meanwhile, there is no doubt that motorization brought about by transport infrastructure investment has contributed to improved economic growth and quality of life (QOL) in developed cities (i.e., cities in wealthy developed countries with higher GDP per capita). Similar to developed cities, developing cities (i.e., cities in developing countries with low GDP per capita) also have the right to guaranteed economic growth and QOL; policies promoting motorization are still required there.

From the viewpoint of global warming, both developed and developing cities should make collaborative efforts to reduce energy consumption by the transport sector to achieve a low-carbon society. Each city therefore must implement appropriate policies for environmentally sustainable transport (EST). In line with the Kyoto Protocol, it is quite important for developing cities not only to minimize environmental burdens but also to maintain the level of mobility. Policy decision makers should seek solutions to the mutual exclusiveness of these two policy goals. The concept of "eco-efficiency" proposed by WBCSD in 1992 (Verfaille and Bridwell 2000), which is concerned with creating more value with less impact, seems useful for capturing the balance between economic growth and environmental conservation. Thus, the second half of this chapter attempts to expand the concept of "eco-efficiency" to develop an environmental efficiency (EE) model based on a data envelopment analysis (DEA) cost-efficiency model focusing on transport systems. The basic ideas behind DEA date back to Farrell (1954), but the recent series of discussions began with articles by Charnes et al. (1978). In addition, Coelli et al. (1997), and Cooper et al. (1999) offer well-organized and systematic overviews. In this chapter, the EE model is estimated using four-wave panel data collected from 46 cities all over the world (Newman and Kenworthy 1999; Kenworthy et al. 2000). Finally, models are applied to evaluate policies for efficient energy consumptions.

1.2 Indicators of Sustainable Development

1.2.1 Existing Indicators

As Bossel (1999) argued, sustainable development has become a widely recognized goal for human society ever since deteriorating environmental conditions in many parts of the world indicated that sustainability might be at stake. To understand the current situation, appropriate indicators are needed. Finding an appropriate set of indicators of sustainable development for a community, city, region or country, or even the world, is not an easy task. Here, we briefly review the main indicators of sustainable development, including:

1. The Genuine Progress Indicator (Redefining Progress 1999),
2. Millennium Development Goals (UNDP 2003),
3. Indicators of Sustainable Development by UNDSD (2000),
4. Dashboard by IISD (2002),
5. Indicators of Sustainable Community (AtKisson 1996),
6. Environmental Sustainability Index (World Economic Forum 2001), and
7. Environmental Indicators by European Environmental Agency (EEA 1999).

1.2.1.1 The Genuine Progress Indicator

Redefining Progress (1999), a nonprofit, nonpartisan public policy institute, argued that GDP was badly flawed as a measure of economic health because it counts only monetary transactions as economic activity. It ignores much of what people value and activities that serve basic needs, such as the value of leisure time spent on recreation, relaxation, or with family and friends, crucial contributions from the environment, such as pure air and water, and environmental costs of economic activities. To address the inadequacies of GDP, a new measure of the economic well-being of the nation, the Genuine Progress Indicator (GPI) was developed in 1994 by Redefining Progress. It has been measured for each nation from 1950 to the present. The contents of GPI include crime and family breakdown, household and volunteer work, income distribution, resource depletion, pollution, long-term environmental damage, changes in leisure time, defense expenditure, lifespan of consumer durables and public infrastructure, and dependence on foreign assets.

1.2.1.2 Indicators for Millennium Development Goals

According to Segnestam (2002), the Development Assistance Committee of the Organisation for Economic Co-operation and Development developed the indicators for the so-called International Development Goals (IDGs) initiative, inviting the United Nations, the World Bank and the International Monetary Fund to become partners in 1996. Over the 4 years that followed, five working groups discussed indicators for issues such as poverty, education, gender, infant and child mortality, maternal health, HIV/AIDS, malaria and other diseases, the environment, and global partnership. At a later stage, the name of the targets changed from IDGs to MDGs (Millennium Development Goals). Each goal has a number of identified targets. In total, eight goals and 18 targets were finally proposed. In 2000, the UN Millennium Declaration, adopted at the largest gathering of heads of state ever held, committed countries—rich and poor—to doing all they could to eradicate poverty, to promote human dignity and equality and to achieve peace, democracy and environmental sustainability (UNPD 2003).

1.2.1.3 Indicators for Sustainable Development

Indicators for monitoring progress toward sustainable development are needed to assist decision makers and policy makers at all levels and to increase focus on sustainable development. Beyond the commonly used economic indicators of well-being, however, social, environmental and institutional indicators must also be taken into account to arrive at a broader, more complete picture of societal development. At its third session in 1995, the Commission on Sustainable Development (CSD) of the United Nations initiated the development of indicators for the measurement of sustainable development. Major areas cover social, environmental, economic and institutional aspects. A working list of 134 indicators was selected, and 22 countries volunteered to test their applicability, using a framework based on environmental (sustainable development) themes (UNDSD 2000).

1.2.1.4 Dashboard

Dashboard was proposed by the International Institute of Sustainable Development (IISD). Dashboard consists of four categories of society, environment, economy and institutions, for which the index is calculated from individual indicators (IISD 2002). The social category includes 18 indicators of factors such as poverty, equity, unemployment, child weight, child mortality, life expectancy, safe water, crowding, population growth and urbanization. The environmental category has 19 indicators, including measures of CO_2, cropland, forest area, key ecosystems, mammals and birds and protected areas. The economic category includes 13 indicators such as GNP, ODA (Official Development Assistance), and measures of energy use and efficiency, waste, recycling, and car use. Finally, the institutional category has eight indicators, which are of factors such as SD strategy, SD membership, Internet, telephones, R&D expenditure, disasters (human cost and economic damage) and SD indicator coverage. Institutional aspects may be used to measure the capacity of government.

1.2.1.5 Indicators of Sustainable Community

A famous and frequently imitated example is the set of indicators of sustainable development for the city of Seattle, Washington. This set is the result of a long process of discussion and development, involving intensive citizen participation (AtKisson 1996). When Sustainable Seattle participants first began meeting in the early spring of 1991, sustainability was a new concept to most people in public life. For many nations, the Brundtland Commission report became a call to action. However, the US government expressed little interest in the concept, leaving most members of the public uninformed. However, Seattle's Mayor and the President of its City Council both made statements to the press that were strongly supportive of the project. After 5 years of steady work by legions of volunteers, Sustainable Seattle had overcome numerous barriers, including the need:

1. To build trust among diverse participants,
2. To establish credibility and legitimacy in the eyes of decision makers and the media,
3. To mobilize and retain highly skilled volunteers,
4. To include the creative participation of hundreds of citizens, and
5. To meet the technical challenge of finding and presenting data for 40 long-term trends.

Since its inception, production of the indicators report—now projected to be updated every 2–3 years (AtKisson 1996)—Sustainable Seattle Indicators has expanded to cover environment, population and resources, economy, youth and education, and health and community.

1.2.1.6 Environmental Sustainability Index

The Environmental Sustainability Index (ESI), sponsored by the World Economic Forum, is designed to provide national-level figures on environmental sustainability for, at present, 122 nations across the globe (World Economic Forum 2001). The ESI is an initiative of the Global Leaders of Tomorrow Environment Task Force of the World Economic Forum in collaboration with the Yale Center for Environmental Law and Policy (YCELP) of Yale University and the Center for International Earth Science Information Network (CIESIN) of Columbia University. The ESI consists of five dimensions or components: environmental systems, reducing environmental stresses, reducing human vulnerability, social and institutional capacity and global stewardship. The ESI was developed partly based on the pressure–state–response (PSR) or driving force–state–response (DSR) frameworks, which have their origin in work by the OECD, the Canadian government and the UNEP (Hammond et al. 1995; OECD 1999). Pressure on the environment from human and economic activities leads to changes in the state or environmental conditions. These changes to prevailing conditions may provoke members of society to alleviate the pressures on, and to improve the state of the environment (OECD 1999). In this light, the environmental stresses component of the ESI corresponds to the pressure component of the PSR framework. The environmental systems component of the ESI corresponds to the state component of the PSR framework, and to some extent, the same can be said about the human vulnerability component of the ESI, which reflects the state of the human system. Finally, social and institutional capacity and global stewardship reflect different aspects of the response component of the PSR framework. In this context, it should be remarked that the global stewardship component also contains some typical pressure variables in its protecting international commons indicator (Niemeijer 2002).

1.2.1.7 Environmental Indicators of the European Environmental Agency

The European Environmental Agency (EEA) has developed various indicators related to agriculture, air, biodiversity change, climate change, coasts and seas, energy, fisheries, households, nature, soil, tourism, transport, and water, based on the DPSIR framework proposed by OECD (VRDC 2001), which is described below. EEA (1999) argues that indicators can be classified into four simple groups, which address the following questions.

- What is happening to the environment and to humans? (Descriptive indicators)
- Does it matter? (Performance indicators)
- Are we improving? (Efficiency indicators)
- Are we, on the whole, better off? (Total welfare indicators)

Descriptive indicators describe the actual situation with regard to the main environmental issues, such as climate change, acidification, toxic contamination and volume of waste produced in relation to the geographical levels at which these issues manifest themselves. Performance indicators compare actual conditions with a specific set of reference conditions. They measure the discrepancy between the current environmental situation and the desired situation (target). Most countries and international bodies currently develop performance indicators to monitor their progress toward environmental targets. On the other hand, efficiency indicators provide insight into the efficiency of products and processes, in terms of the resources used and the emissions and waste generated per unit of desired output. The most commonly used efficiency indicators express the amount of emissions or energy used per capita or per unit of GDP. Total welfare indicators are used to measure total sustainability, such as the Index of Sustainable Economic Welfare (ISEW).

From the above-mentioned review, it is obvious that most of the existing indicator systems have been developed at the national level, and relevant indicators at the city level are very limited. This becomes a barrier to translating the concept of sustainability into practical dimensions of the real world. Furthermore, interdependences among indicators are not explicitly represented, although the concepts have been discussed. Therefore, this study focuses on the development of sustainability indicators at the city level, explicitly and systematically incorporating interdependences among indicators.

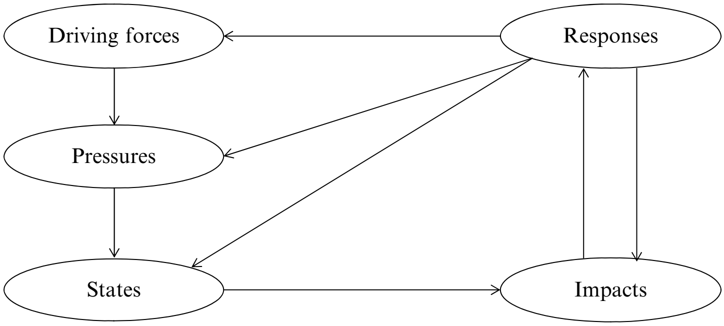


Fig. 1.1 DPSIR framework developed by OECD. *Source*: OECD (1999) and VRDC (2001)

1.2.2 Methodologies of Indicator Development

It is well known that developing any type of model is subject to the constraints of data availability. This is also true for the development of sustainability indicators. Work on the development of indicators ranges from exploiting existing data to describe the state of the environment best to determining the best possible theoretical indicators as points of departure for future data collection and stocktaking (Niemeijer 2002). The former is called the data-driven approach, which argues that data availability is the central criterion for indicator development and for data to be provided for all selected indicators. The latter is called the theory-driven approach, which focuses on selecting the best possible indicators from a theoretical point of view, while data availability is considered to be only one of the many aspects to take into account. Here, two representative methodologies related to the indicator development in this chapter are summarized. One is a data-driven approach, called the DPSIR framework (OECD 1999; VRDC 2001), and the other is a theory-driven approach, called the system approach (Bossel 1999).

1.2.2.1 Data-Driven Approach: DPSIR Framework

The DPSIR framework (see Fig. 1.1) was proposed by the OECD (1999). It is widely applied to sustainable development problems at the national level. In this framework, social and economic developments exert pressure (P) on the environment, resulting in changes to the state (S) of the environment such as the provision of adequate conditions for health, resources availability and biodiversity. This has impacts (I) on human health, ecosystems and materials that may elicit a societal response (R) that feeds back to the driving forces (D) or affects the state of the environment directly.

To be specific, indicators of driving forces describe social, demographic and economic developments in societies and the corresponding changes in lifestyles, overall levels of consumption and production patterns. Primary driving forces are population growth and developments in the needs and activities of individuals. Pressure indicators describe developments in the release of substances (emissions), physical and biological agents, the use of resources and the use of land. Examples of pressure indicators are CO_2 emissions in each sector, the use of rock, gravel and sand for construction and the amount of land used for roads. State indicators describe the quantity and quality of physical phenomena (such as temperature), biological phenomena (such as fish stocks) and chemical phenomena (such as atmospheric CO_2 concentrations) in a given area. The state of the environment changes in response to pressure. These changes then have impacts on its social and economic functions, such as the provision of adequate conditions for health, resource availability and biodiversity. Response indicators refer to responses by groups (and individuals) in society, as well as government attempts to prevent, compensate, ameliorate or adapt to changes in the state of the environment (VRDC 2001).

1.2.2.2 A Theory-Driven Approach: The System Approach

Sustainable urban development involves a complex decision-making process. To identify the vital aspects of such decisions properly, the system approach is preferred. Bossel (1999) described a system as anything composed of elements connected in a characteristic system structure. This configuration of elements allows a system to perform specific functions in its environment. Bossel (1999) proposed the application of orientation theory, which was developed in the 1970s in an effort to understand and analyze divergent visions of the future and normative interests of various societal actors (political parties, industry and environmental NGOs), and defined criteria and indicators for sustainable development (Bossel 1987). Six fundamental properties are relevant: normal environmental state, resource scarcity, variety, variability, change and other systems. These environmental properties can be viewed as imposing certain requirements and restrictions on systems, which orient their functions, development and behavior. Basic orientors consist of environment-determined and system-determined orientors. The former includes existence, effectiveness, freedom of action, security, adaptability, and coexistence. The latter includes reproduction, psychological needs and responsibility (Bossel 1999). These basic orientors are unique in the sense that one orientor cannot be substituted for another. Bossel (1999) argues that orientation theory could be used to develop a general method for finding a comprehensive set of indicators of sustainable development.

Although a theory-driven approach is desirable, this study proposes a data-driven approach, considering the limitation of available data in developing countries. However, the most serious disadvantage of DPSIR is that it neglects the systemic and dynamic nature of processes, and their embedding in a larger total system with many feedback loops. To take full advantage of the data-driven approach and to overcome its shortcomings, the use of structural equation modeling seems promising.

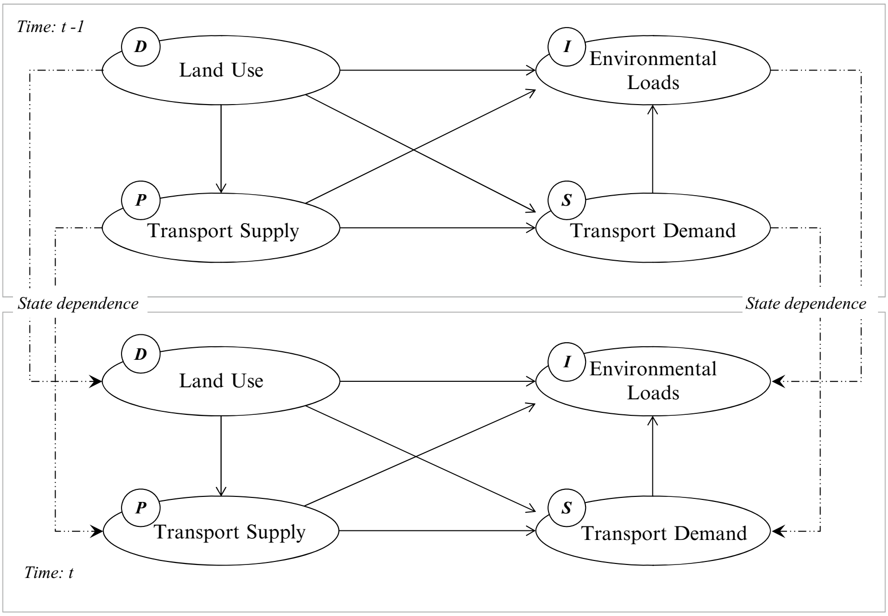


Fig. 1.2 Conceptual dynamic model structure of DPSIR framework

1.2.2.3 Structural Equation Models

Considering the data availability in developing countries, and aiming to capture the complex cause–effect relationships existing in the measurement of sustainability, in this study, we propose to apply a structural equation model, which is a set of simultaneous equations. Structural equation models have proved to be useful in solving many substantive research problems in social and behavioral sciences. Such models have been used in the study of macroeconomic policy formation, intergenerational occupational mobility, racial discrimination in employment, housing and earnings, studies of antecedents and consequences of drug use, scholastic achievement, evaluation of social action programs, voting behavior, studies of genetic and cultural effects, factors in cognitive test performance, consumer behavior, and many other phenomena, including transportation. Methodologically, the models play many roles, including simultaneous equation systems, linear causal analysis, path analysis, structural equation models, dependence analysis, and cross-lagged panel correlation techniques (Jöreskog and Sörbom 1989). Structural equation models are used to specify the phenomenon under study in terms of putative cause–effect variables and their indicators.

As mentioned previously, sustainability has various dimensions, including economic, environmental, material, ecological, social, legal, cultural, political and psychological. It is desirable to represent comprehensively the cause–effect relationships existing in the concept of sustainability based on a theory-driven approach such as the system approach. However, it remains difficult to apply a theory-driven approach because of data unavailability. In this sense, it is realistic to adopt the data-driven approach. This study proposes a dynamic structural equation model (see Fig. 1.2), where *land use*, *transport supply* and *demand*, and *environmental loads*, defined as latent variables, are introduced to represent urban sustainability. The model structure is similar to that of the DPSIR framework. The difference is that the new model represents the endogenous cause–effect relationships among the four elements related to urban sustainability. In addition, dynamic cause–effect relationships are also incorporated in the model based on the concept of state dependence, which indicates the influence of a dependent variable at time $t\text{–}1$ on its value at time t.

1.3 A Worldwide Case Study of Developed and Developing Cities

1.3.1 Data from 46 Cities and Findings

This analysis uses data from 46 cities in developed and developing countries, collected by Kenworthy et al. (2000). These include an extensive set of land-use, transportation and energy data on 46 cities around the world at four points in time (1960, 1970, 1980 and 1990). The cities are shown in Table 1.1. The characteristics of the main factors in the data are shown in Fig. 1.3 (population), Fig. 1.4 (vehicle ownership), Fig. 1.5 (length of roads), Fig. 1.6 (parking spaces in CBD), Figs. 1.7 and 1.8 (travel distance by car and public transport systems), and Figs. 1.9 and 1.10 (energy use by car and public transport systems). The data in these figures suggest that because of the current limited supply of transportation, environmental issues in developing countries will be further worsened by rapid population growth and vehicle ownership.

1.3.2 Dynamic Evaluation Model of Cause–Effect Relationships Among Indicators

Although Kenworthy et al. (2000) collected an extensive set of land-use, transportation and energy data, it remains difficult to provide sufficient information for the DPSIR framework, which was developed to evaluate sustainability at the national level.

Table 1.1 Target cities used in the analysis

Region	Number	Cities
United States	12	Boston, Chicago, Detroit, Houston, Los Angels, New York, Phoenix, Portland, Sacramento, San Diego, San Francisco, Washington
Australia	6	Adelaide, Brisbane, Canberra, Melbourne, Perth, Sydney
Canada	6	Edmonton, Montreal, Ottawa, Toronto, Vancouver, Winnipeg
Europe	9	Copenhagen, Frankfurt, Hamburg, Landon, Munich, Paris, Stockholm, Vienna, Zurich
Wealth Asia	3	Hong Kong, Singapore, Tokyo
Developing Asia	6	Bangkok, Jakarta, Kuala Lumpur, Manila, Seoul, Surabaya

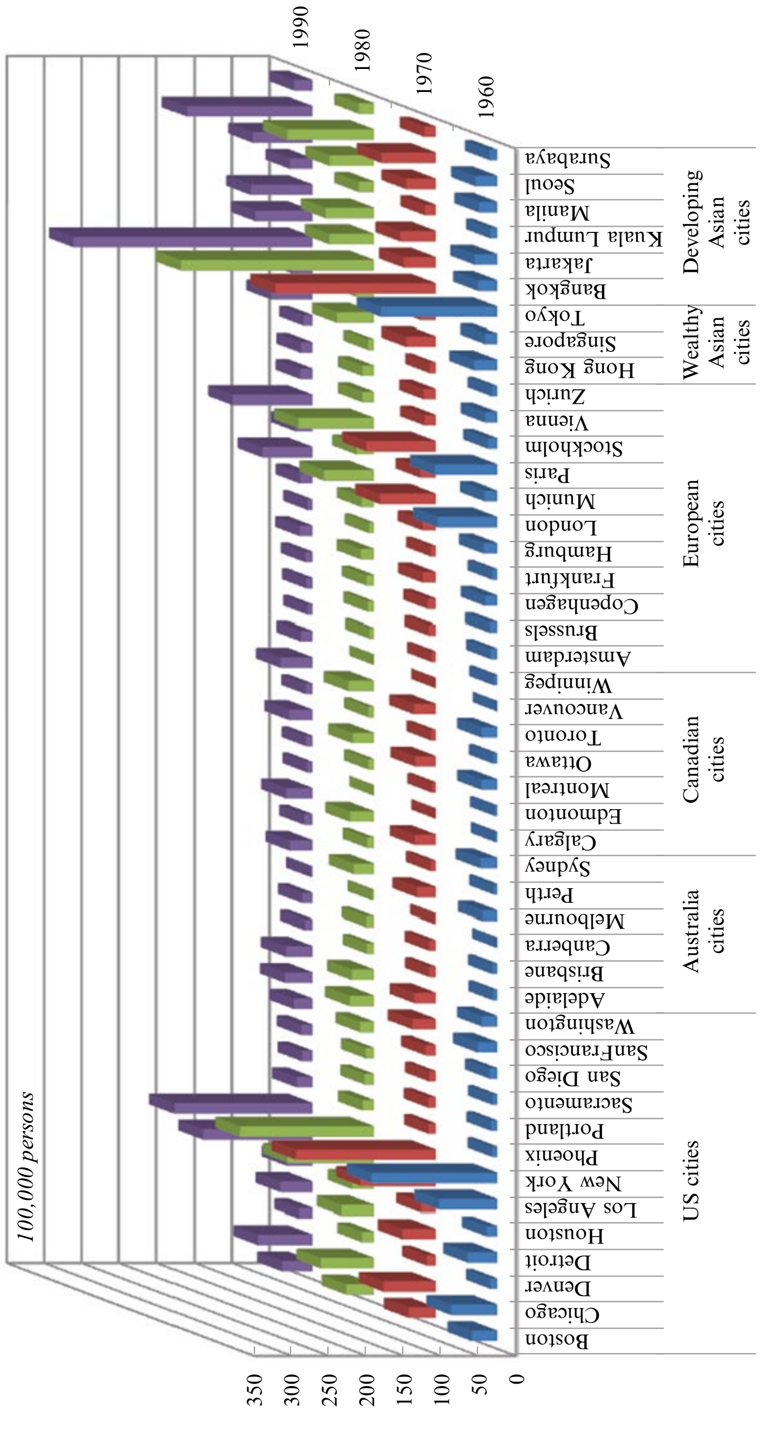


Fig. 1.3 Population growths in developed and developing cities

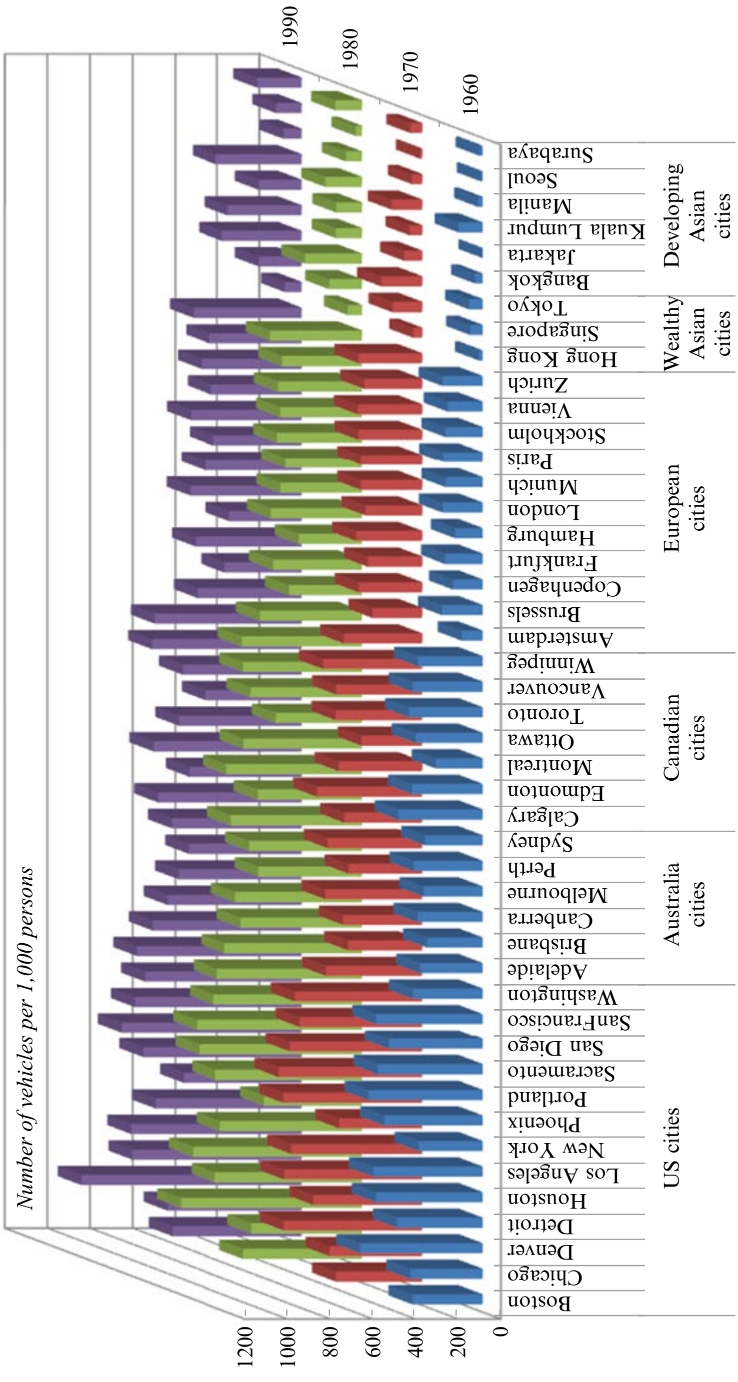


Fig. 1.4 Vehicle ownership in developed and developing cities

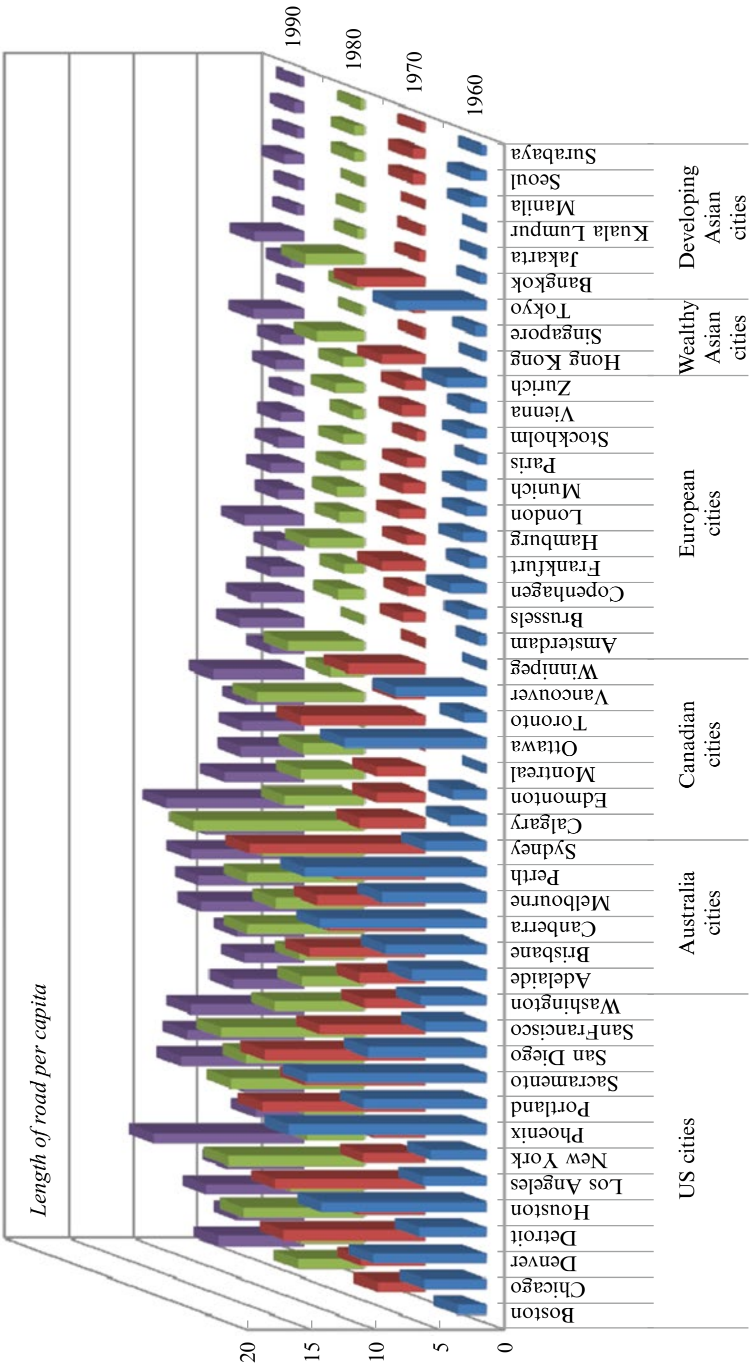


Fig. 1.5 Length of road in developed and developing cities

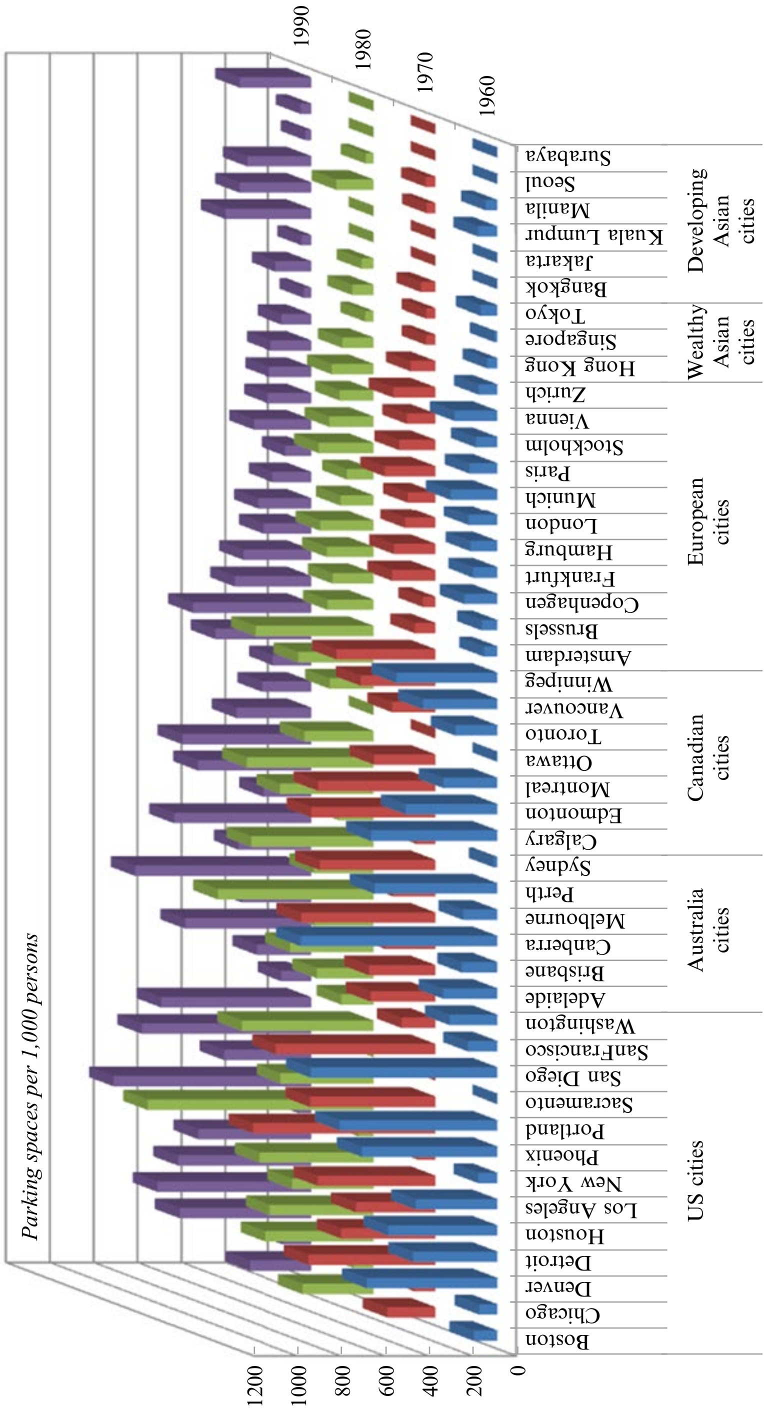


Fig. 1.6 Parking spaces at CBD in developed and developing cities

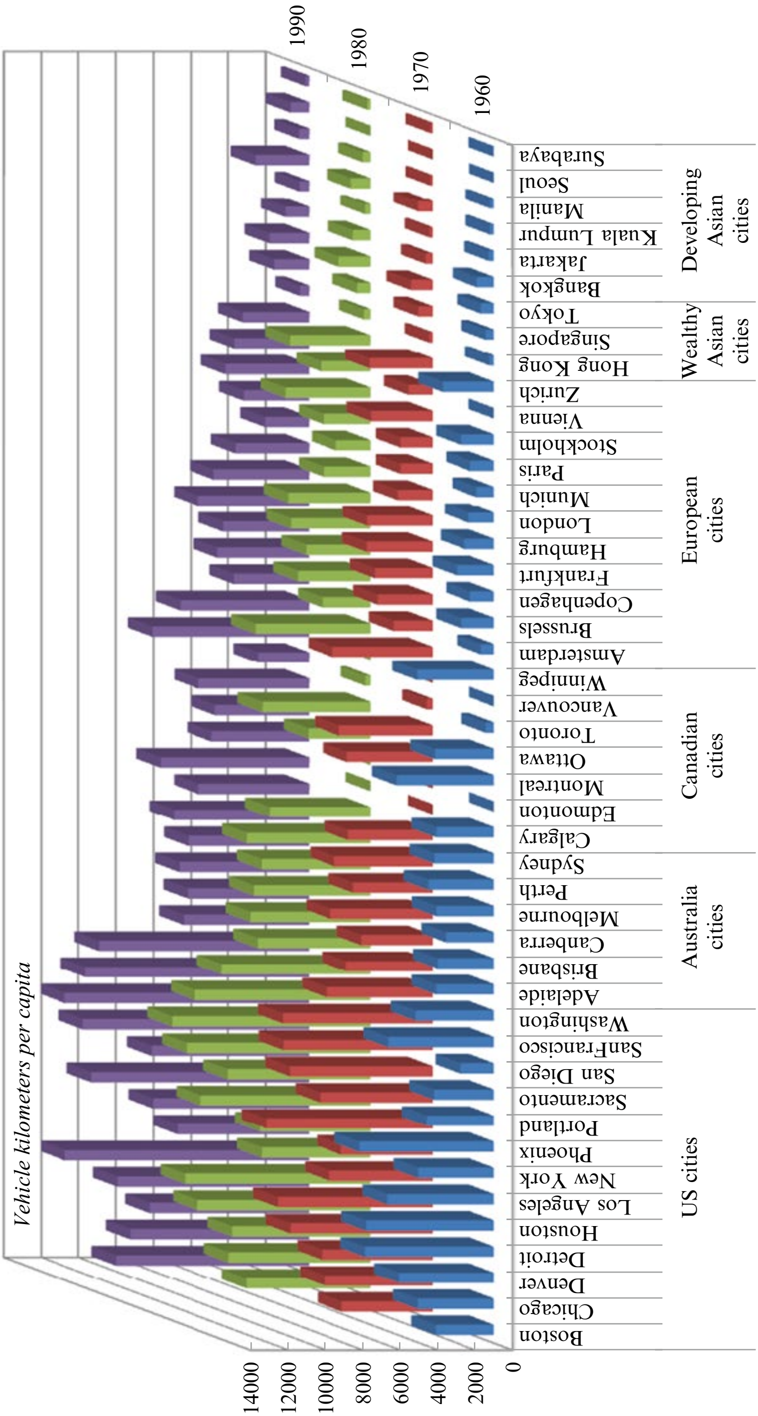


Fig. 1.7 Travel distance by passenger cars in developed and developing cities

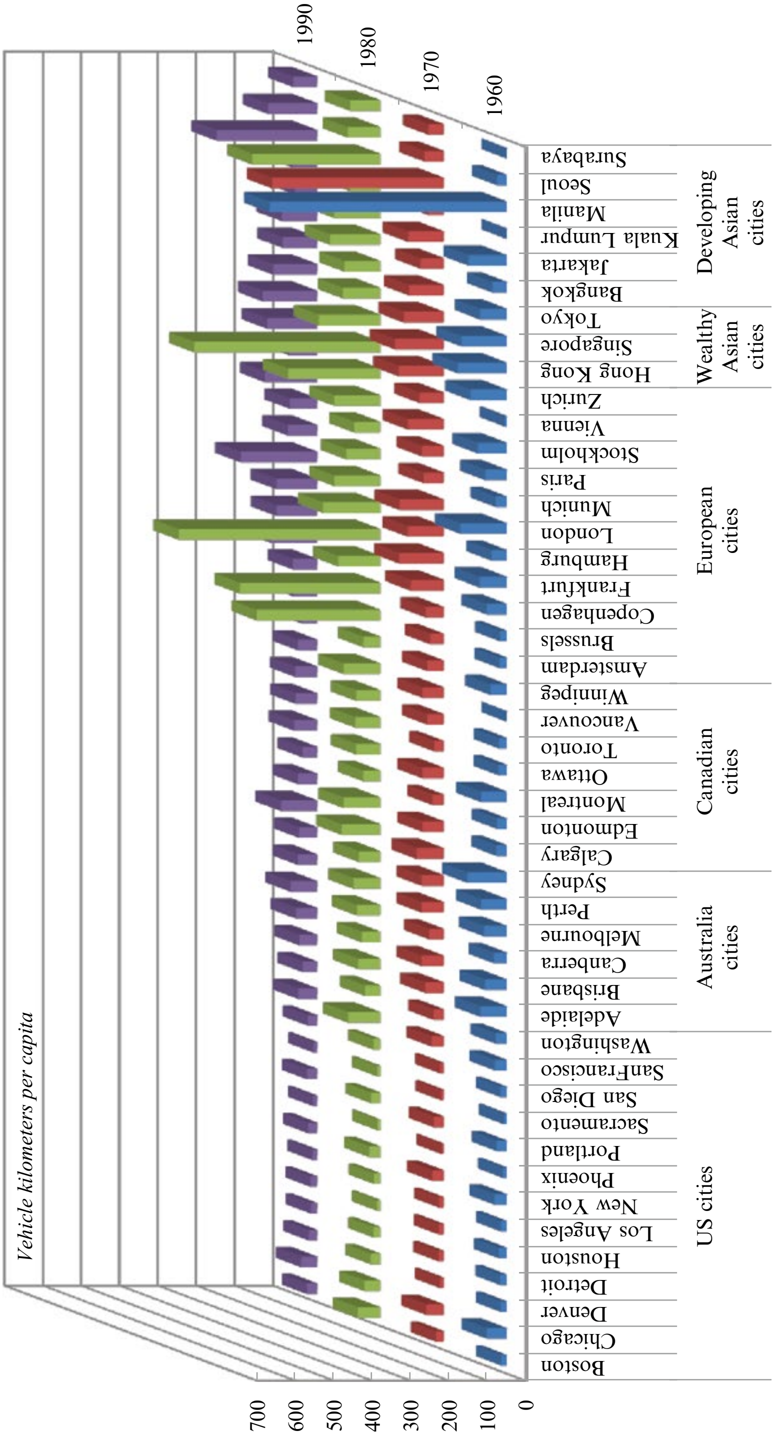


Fig. 1.8 Travel distance by public transport systems in developed and developing cities

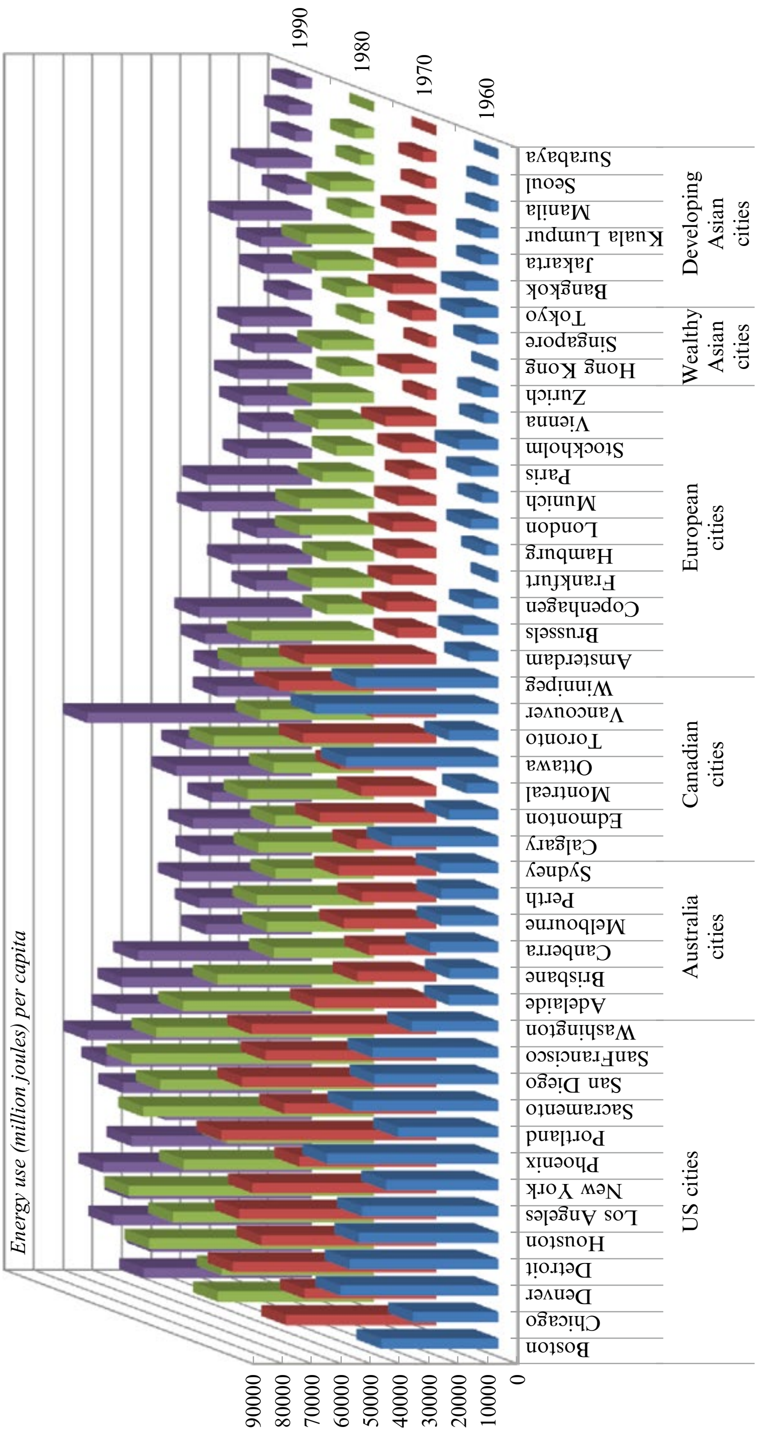


Fig. 1.9 Energy use by passenger cars in developed and developing cities

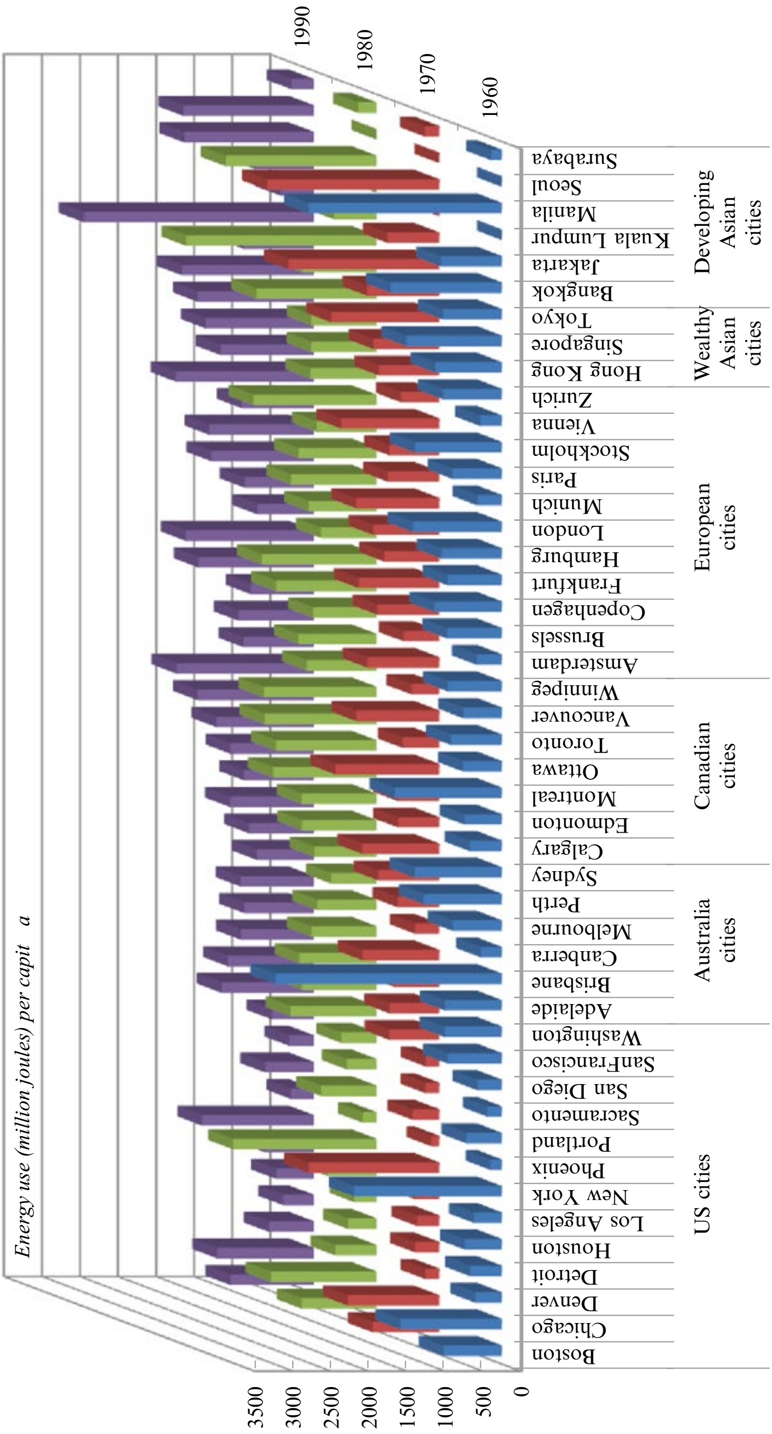


Fig. 1.10 Energy use by public transport systems in developed and developing cities

The data were adopted in this study because they also include information from different points in time, which can be used to describe the dynamic cause–effect relationships among land use, transportation and energy use. Although as mentioned above, sustainability has economic, environmental, material, ecological, social, legal, cultural, political and psychological dimensions, this chapter evaluates urban sustainability based on land use, transportation and energy consumption (an alternative variable for environmental loads) using available data. Transportation is further divided into transport demand and transport supply, because these two new latent variables represent two contrasting aspects of transportation system.

Because a relatively large amount of data from 1960 is missing, this study only uses data from the other three points in time (i.e., 1970, 1980 and 1990) for the initial model estimation, before clarifying a suitable imputation method for the missing data. A structural equation model is first applied to describe the pooled data from 1970, 1980 and 1990. Based on a preliminary trial-and-error analysis, the latent "land use" variable is represented by the proportion of the population in the CBD, the proportion of the population in inner areas, the proportion of jobs in the CBD, and the proportion of jobs in inner areas. "Transport supply" is defined as the parking spaces per 1,000 people in the CBD, the length of road per capita and the vehicle ownership per 1,000 people. VKT (vehicle kilometers traveled) ratios between car and other travel modes (bus, rail and other public transport (PT) systems) are used to describe the latent "transport demand" variable. Finally, the observed variables for energy consumption include energy consumption ratios between car and other travel modes.

The model is estimated by applying the AMOS 4.0 software (Arbuckle and Wothke 1999), and the estimation results are shown in Fig. 1.11. Standardized results are shown to compare the influences of factors directly with different scales. They are calculated based on the original estimated parameters and their standard deviations obtained from the nonstandardized results. The calculated GFI (0.700) and AGFI (0.600) suggest that the resultant model has a satisfactory goodness-of-fit index. Most of the estimated parameters are statistically significant. Moreover, the signs of the parameters empirically support the assumptions mentioned in the previous paragraph.

Based on the above cross-sectional estimation results from the pooled model, it can be concluded that increasing urban density in central areas could greatly improve the level of sustainability compared with that under the control transportation systems policy. This finding from a cross-sectional analysis supports the widely accepted urban planning concept, that of the compact city.

To confirm the consistency of this observation over time and further to capture the dynamic characteristics of urban sustainability, a dynamic model with the structure shown in Fig. 1.12 was established. It is assumed that cause–effect parameters related to land use, transport supply, transport demand and energy consumption are invariant over time. Instead, to represent the temporal change in the level of sustainability, the state dependence parameter was introduced with respect to each latent variable. The assumption of invariance was made because of the limited sample size used in this study.

Each latent variable was first calculated from the above-mentioned pooled model (Fig. 1.11). Then, based on these calculated latent variables, the dynamic model was

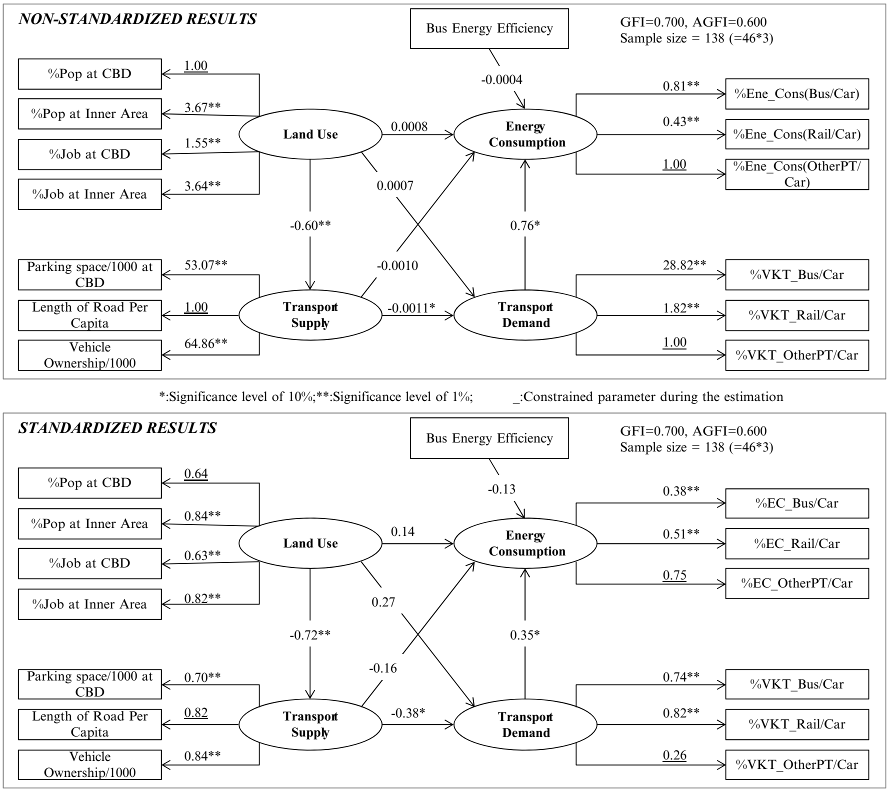
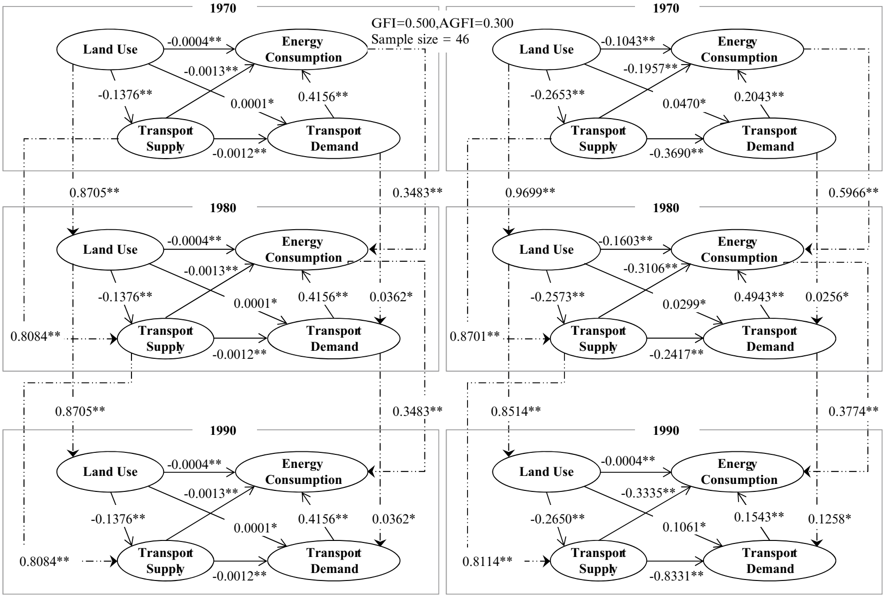


Fig. 1.11 Standardized and non-standardized estimation results of the pooled model**.** *: Significance level of 10 %; **: Significance level of 1 %; __: Constrained parameter during the estimation

estimated, with the results shown in Fig. 1.12. Here, it is further assumed that parameters of state dependence do not change over time. This assumption makes future prediction possible. This is a convenient way to evaluate urban policies, especially in developing countries.

One can observe that all the parameters of state dependence are statistically significant and have positive signs. This justifies introducing state dependence. All other parameters are significant and have the expected signs. These results suggest the validity of the proposed model structure. However, the model is not sufficiently accurate. There may be several reasons for this. The limited sample size (46 cities in this study) can be regarded as the major reason. Because it is usually difficult to collect the relevant data, especially time series data at the city level, more efficient estimation methods should be developed for small sample sizes. At the same time, carefully transforming some explanatory variables might be helpful. Because the main purpose of this study is to confirm the effectiveness of structural equation models in evaluating urban sustainability, the above issues are left for future research.

To evaluate the dynamic characteristics of urban sustainability, the total effects of the dynamic model (Fig. 1.12) are calculated and shown in Table 1.2. The total



(a) Non-standardized estimation results (b) Standardized estimation results

Fig. 1.12 Standardized and non-standardized estimation results of the dynamic model

effects vary over time because of the accumulating effects of the state dependence parameter, although it is assumed to be invariant over time. *Energy consumption* in 1980 is most strongly influenced by *energy consumption* in 1970. *Transport supply* in 1970 is ranked in second place. This implies that *energy consumption* in 1980 is mainly determined by energy consumption behavior and transport supply policies in previous times. On the other hand, the top three factors affecting *energy consumption* in 1990 are all from *transport supply*, especially from that in previous times. This means that transport supply policies supporting economic activities in the past largely determined energy consumption patterns in 1990. Contrary to the observation from the cross-sectional model, the influence of *land use* on *energy consumption* is very limited in the dynamic context. This study estimated other types of model structures by relaxing the above-mentioned assumptions; however, the conclusions about "land use" were the same. As discussed in Sect. 1.2, the existing indicator frameworks of sustainable development have ignored the quantitative cause–effect relationships among indicators. In contrast, the proposed dynamic model based on the data collected at the city level can produce relevant sustainability indicators explicitly incorporating the endogenous cause–effect relationships. Use of combined data from the developed cities could provide some good benchmarks for improving their sustainability.

Table 1.2 Standardized total effects from dynamic model

	From										
To	LU in 1970	LU in 1980	LU in 1990	TS in 1970	TS in 1980	TS in 1990	TD in 1970	TD in 1980	TD in 1990	EC in 1970	EC in 1980
EC in 1970	–0.023			–0.271			0.204				
EC in 1980	0.054	–0.035		–0.540	–0.430		0.135	0.494		0.570	
EC in 1990	0.171	0.052	–0.039	–0.534	–0.542	–0.462	0.051	0.206	0.154	0.225	0.377
TD in 1970	0.145			–0.369							
TD in 1980	0.149	0.092		–0.220	–0.242		0.026				
TD in 1990	0.613	0.464	0.327	–0.616	–0.706	–0.833	0.003	0.126			
TS in 1970	–0.265										
TS in 1980	–0.480	–0.257		0.870							
TS in 1990	–0.609	–0.434	–0.265	0.706	0.811						
LU in 1980	0.970										
LU in 1990	0.826	0.851									

EC energy consumption, *TD* travel demand, *TS* travel supply, *LU* land use

1.4 Environmental Efficiency

1.4.1 Methodological Definition

Some studies have addressed EE in the transport field. Senbil et al. (2005) employed Stochastic Frontier Analysis (SFA) to evaluate the structure of transport energy consumption and used a Tobit model to clarify factors that significantly affect EE. Pitt and Smith (2003), Feng et al. (2007) and Ahmad et al. (2009) also evaluated EE in the transport sector using SFA or DEA. Although these studies adopted different approaches, they commonly defined EE as the ratio of the transport index (input) and environmental index (output).

The above definition, however, has some unresolved problems. One is the diversity of transport systems in each city. EE is clearly influenced by several factors. The weight of each factor may also vary with the levels of infrastructure development, transport investment, land-use patterns, and so on. However, existing studies usually assume equal weights for all factors. Ignoring the diversity of transport systems in the determination of energy-saving countermeasures may incorrectly lead to the establishment of a uniform target of efficiency for all cities. To solve this problem, a new EE model needs to be built to deal with adjustable weights.

Another problem is intercity heterogeneity of the energy consumption structure. In general, cities have different historical paths of development and investment for urban facilities and transport infrastructure, and consequently have different attributes (e.g., different levels of infrastructure development, population densities and distributions, and land-use patterns). They may also set varying targets depending on their philosophies, as set forth in city perspectives and master plans. The factors influencing current energy consumption may not be stable across cities. However, existing SFA and DEA models based on the simple ratio between input and output cannot accommodate the heterogeneous structure of energy consumption in detail. Thus, a new EE model is required to cope with this methodological issue.

Responding to the above problems, this study proposes a new cause–effect structure of energy consumption based on the DEA cost-efficiency model (Camanho and Dyson 2005; Fukuyama and Weber 2003). To reflect the intercity diversity of transport systems, all cities will be divided into homogeneous groups before model estimation. Moreover, to address the intercity heterogeneity of the energy consumption structure, a new EE model consisting of measurement equations that capture causal factors and their inconstant weights is proposed.

In the cost-efficiency model described above, it is supposed that input indexes can be expressed as a function of factors related to travel demand and that energy intensity can be set as a cost index with an input unit value. In concrete terms, average annual trip distances (in kilometers) for public and private transport modes are used as input indexes, and energy intensities that indicate the amount of energy consumption (in megajoules) per passenger–kilometer for each mode are employed as cost indexes. By multiplying the input indexes by the cost indexes, the total amount of energy consumed is obtained. Moreover, the average trip speed (the average of two modes, in kilometers per hour) is used as the output index to explain the level of mobility at the city level.

The proposed DEA cost-efficiency model assumes *m* inputs, *s* outputs and *n* cities. The EE of city *k* (EE_k) can be expressed as Eq. (1.1):

$$\mathrm{EE}_k = \frac{c_k^*}{c_k} = \frac{\sum_{i=1}^{m} p_{ik} x_i^*}{\sum_{i=1}^{m} p_{ik} x_i} \tag{1.1}$$

where

x_{ik} : observed input index *i* for city *k* $(i = 1, 2, \ldots, m)$,
p_{ik} : observed cost per unit input *i* for city *k*,
c_k : observed energy consumption,
c_k^* : optimum energy consumption that minimizes the total energy consumption for public and private transport modes while securing the current level of output index, and
x_i^* : optimized amount of input *i* obtained by following the cost-efficiency model [see Eqs. (1.2)–(1.7)].

$$\text{Minimize } \sum_{i=1}^{m} p_{ik} x_{ik} \tag{1.2}$$

subject to

$$-\sum_{j=1}^{n} x_{ij} \lambda_j + x_i \geq 0 \left(i = 1, 2, \ldots, m\right) \tag{1.3}$$

$$\sum_{j=1}^{n} y_{rj} \lambda_j \geq y_{rk} \left(r = 1, 2, \ldots, s\right) \tag{1.4}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{1.5}$$

$$\lambda_j \geq 0 \left(j = 1, 2, \ldots, n\right) \tag{1.6}$$

$$x_i \geq 0 \left(j = 1, 2, \ldots, n\right) \tag{1.7}$$

where

x_{ij} : observed input index *i* for city *j*,
y_{rj} : observed output index *r* for city *j* $\left(j = 1, 2, \ldots, s\right)$, and
λ_j : weight of *j*th city (a nonnegative *n*-dimension vector).

Equation (1.2) includes the input vector $\mathbf{X} = (x_1, x_2, \ldots, x_m)^T$ as a set of causal factors that vary across cities. It minimizes the total amount of energy consumption on the basis of the vector of energy consumption intensity, $\mathbf{P}_k = (p_{1k}, p_{2k}, \ldots, p_{mk})$.

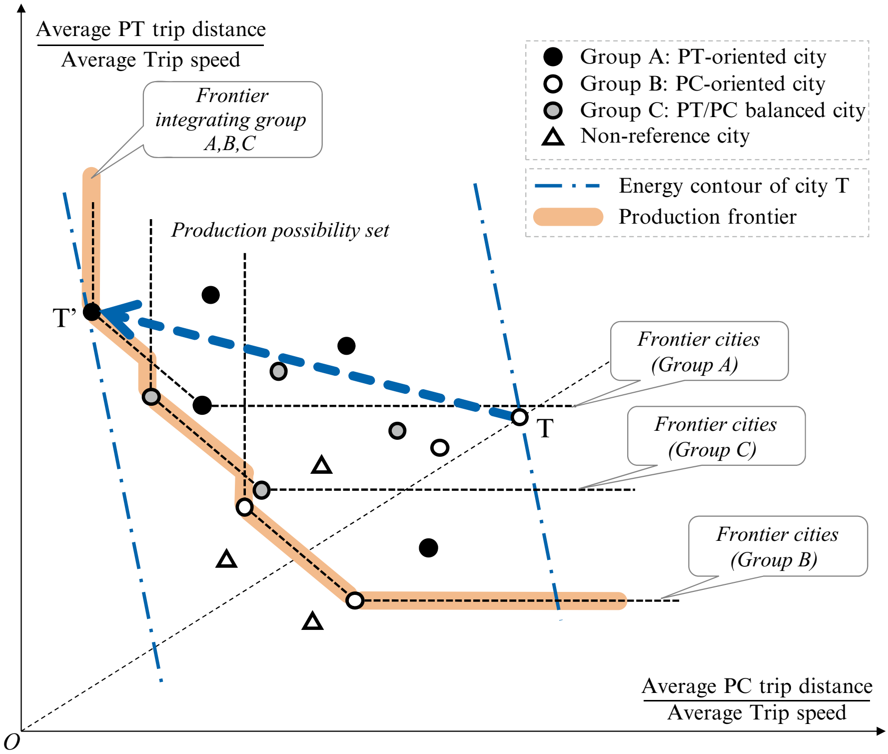


Fig. 1.13 Concept of environmental efficiency model

1.4.2 Development of Environmental Efficiency Model

Because the energy intensity of public transport (PT) is superior to that of the private car (PC), it is generally necessary to reduce PC use more than PT use. It is unlikely that PT infrastructure (e.g., for railway and bus networks) that has already been constructed would be abandoned to improve the inner city energy consumption structure. Therefore, another condition was added to Eqs. (1.2)–(1.7) that the input index of PT should be maintained as the status quo (Banker and Morey 1986). This condition creates the input index with a political threshold.

Because each city has its own philosophy of transport planning, each city may have different transport mode targets to improve mobility around the whole city. The conventional DEA seeks an optimum solution on the frontier curve by including all PT-oriented, PC-oriented, and PT/PC balanced cities with different attributes. However, it is unreasonable to compromise, because perspectives and approaches to determining a frontier vary between cities.

To solve this problem, this study assumes that a convex set between different groups—that is, the PT-oriented, PC-oriented, and PT–PC balanced cities—is not allowed. Specifically, three frontier curves (see the dashed curves in Fig. 1.13) are first drawn independently on the basis of reference sets of the three groups. They are then combined as an integrated frontier for each group (see the shaded curve with a dashed line in Fig. 1.13). Finally, to measure EE, each city seeks the reference sets all along the integrated frontier curve across the boundary of its own production area. This approach allows development in the city to proceed and enables the effective evaluation of efficiency (Tone 1993).

By this approach, cities should be categorized a priori into several exclusive groups. Cluster analysis was used to identify the groups in this study. The Euclidean distance was calculated on the basis of infrastructure development, such as the road length per capita and the distance travelled by PT per capita. From the analysis, each city was categorized into one of three clusters; PC-oriented, PT-oriented and PT–PC balanced cities, at four points in time from 1960 to 1990 (Table 1.3). Note that for the reason described in the following section, developing cities (defined as cities with GDPs of less than $10,000 per capita at each time point) are not included in the reference sets.

Investment in the transport infrastructure is irreversible because it is not realistic to assume that developed cities that have invested well in their transport infrastructure would reduce their mobility level as occurs in developing cities, even if developing cities are identified as more efficient because their energy consumption is less excessive. Thus, it is also assumed that developing cities belong to the nonreference set. It would be unfeasible to include them in any reference set for evaluating developed cities.

1.4.3 Capturing Temporal Change of Environmental Efficiency

When the EE model is used for cross-section analysis, z_t^t is a solution for z^t in this model. In the case of longitudinal analysis, however, the frontier may shift over a given time period from time t to t+1. Moreover, as shown in Table 1.3, the group to which each city belongs changes over the four periods from 1960 to 1990. In this case, performance at time t should be reevaluated according to the frontier at t+1. The Malmquist approach can be applied to evaluate the frontier shift caused by a technological innovation (Fare et al. 1994).

It is known that the Malmquist index M_k (Malmquist 1953) can be resolved into a catch-up (CU) index with a frontier shift (FS) index, as shown in Eq. (1.8), in which the former refers to the temporal change of distance to the frontier and the latter indicates the temporal shift of the frontier:

$$\begin{aligned} M_k &= \text{CU index} * \text{FS index} \\ &= \frac{F^{t+1}(x^{t+1},\ y^{t+1})}{F^t(x^t,\ y^t)} \cdot \left[\frac{F^t(x^{t+1},\ y^{t+1})}{F^{t+1}(x^{t+1},\ y^{t+1})} \cdot \frac{F^t(x^t,\ y^t)}{F^{t+1}(x^t,\ y^t)} \right]^{\frac{1}{2}} \end{aligned} \tag{1.8}$$

Table 1.3 Classification of cities based on cluster analysis

	1960			1970			1980			1990		
Group[a]	PC	BL	PT	PC	BL	PT	PC	BL	PT	PC	BL	PT
Road length [m/capita]	6.9	2.7	2.0	7.3	4.6	3.1	8.4	5.4	3.4	7.1	5.0	2.2
PT length [m/capita]	24	60	104	21	58	95	18	57	109	25	62	128
Number of city[b]	16	12	3	17	16	5	9	24	5	12	21	7
Adelaide					√			√			√	
Amsterdam	√			√				√			√	
Boston	√			√			√			√		
Brisbane					√			√			√	
Brussels		√			√			√			√	
Calgary	√			√				√			√	
Canberra				√				√			√	
Chicago		√			√			√		√		
Copenhagen		√				√			√			√
Denver	√			√			√			√		
Detroit	√			√			√			√		
Edmonton	√			√				√			√	
Frankfurt		√			√			√			√	
Hamburg		√			√			√			√	
Hong Kong												√
Houston	√			√			√			√		
London			√			√			√			√
Los Angeles		√		√			√			√		
Melbourne					√			√			√	
Montreal		√			√			√			√	
Munich	√				√			√			√	
New York		√			√			√			√	
Ottawa	√			√				√			√	
Paris		√			√			√			√	
Perth					√			√			√	
Phoenix	√			√			√			√		
Portland	√			√			√			√		
Sacramento	√			√			√			√		
San Diego	√			√			√			√		
San Francisco	√			√				√			√	
Singapore												√
Stockholm			√			√			√			√
Sydney					√			√			√	
Tokyo						√			√		√	
Toronto		√			√			√				√
Vancouver	√			√				√			√	
Vienna		√			√			√			√	
Washington	√			√				√		√		
Winnipeg		√			√			√		√		
Zurich			√			√			√			√

[a]*PC* private car oriented, *PT* public transport oriented, *BL* private car and public transport balanced
[b]Developing cities are excluded in cluster analysis, so that total number of cities changes during four decades

$$\left(\begin{array}{l} F^{t}\left(x^{t},\ y^{t}\right) = \dfrac{z_{t}^{t}}{z^{t}} \\ F^{t+1}\left(x^{t+1},\ y^{t+1}\right) = \dfrac{z_{t+1}^{t+1}}{z^{t+1}} \\ F^{t}\left(x^{t+1},\ y^{t+1}\right) = \dfrac{z_{t}^{t+1}}{z^{t+1}} \\ F^{t+1}\left(x^{t},\ y^{t}\right) = \dfrac{z_{t+1}^{t}}{z^{t}} \end{array} \right) \tag{1.9}$$

where $F(x, y)$ indicates the efficiency score of a city with input x and output y. The superscript F indicates the time of the frontier, and the superscripts x and y indicate the times of the input and output indexes, respectively.

If the FS index is less than 1.0, the technologies are retrogressive for the cities. Otherwise, the technology is progressive. If the CU index is less than 1.0, the efficiency score in the corresponding city declines between two time points; otherwise, the efficiency score increases. Therefore, Malmquist indexes calculated before and after the introduction of the sustainable environmental transport policies being studied can be used to measure the effects of the policy instrument.

1.5 Evaluating Environmental Efficiency of Transport Systems

1.5.1 Cross-Sectional Analysis

For the purpose of confirming its applicability to policy analysis, the proposed EE model was used to measure the efficiency of transport systems using data from a database of 46 cities worldwide at four points in time (1960, 1970, 1980, and 1990), as shown in Table 1.4. Because of space limitations, this discussion mostly concerns the results of the analysis for 1990.

The cities *shaded* in Table 1.4 have environmental efficiency scores of 1.0, which means that they are on the frontier. Meanwhile, the cities shown in boldface in Table 1.4 belong to the reference sets in the corresponding groups. Table 1.4 shows that among PT-oriented cities, Copenhagen and Hong Kong are the reference for many cities, not only in the PT-oriented group. These cities therefore hold a dominant position in terms of environmental efficiency. However, the reference sets for two-thirds of the PC-oriented cities are other PC-oriented cities (e.g., Denver, Sacramento, and Winnipeg). This implies that the efficiency scores obtained reflect the characteristics of the individual cities. Los Angeles, which was originally a PC-oriented city, can potentially improve its efficiency by imitating PT-oriented cities. In other words, the city needs to shift from being PC oriented to PT oriented to

Table 1.4 Evaluation of environmental efficiency of transport systems in 1990

City	EE score	Energy consumption (MJ/pkm)		Reference set (lambda)
		Observed	Optimum	
PC-oriented				
Boston	0.667	58,429	38,947	Canberra (0.976), Montreal (0.024)
Chicago	0.519	56,128	29,126	Copenhagen (0.835), Hong Kong (0.165)
Denver	*1.000*	*68,275*	*68,275*	*Denver (1.000)*
Detroit	0.798	62,733	50,068	Denver (0.954), Winnipeg (0.046)
Houston	0.877	71,603	62,767	Denver (0.517), Sacramento (0.483)
Los Angeles	0.424	62,113	26,336	Copenhagen (0.847), Hong Kong (0.153)
Phoenix	0.751	64,661	48,543	Denver (0.775), Winnipeg (0.225)
Portland	0.803	70,709	56,777	Denver (0.676), Winnipeg (0.324)
Sacramento	*1.000*	*76,636*	*76,636*	*Sacramento (1.000)*
San Diego	0.668	67,213	44,900	Denver (0.930), Winnipeg (0.070)
Washington	0.422	60,466	25,514	Copenhagen (0.728), Hong Kong (0.272)
Winnipeg	**0.458**	**39,365**	**18,018**	**Copenhagen (0.363), Hong Kong (0.637)**
PC-PT balanced				
Adelaide	0.608	37,099	22,557	Copenhagen (0.860), Hong Kong (0.140)
Amsterdam	0.617	19,820	12,237	Copenhagen (0.303), Hong Kong (0.697)
Brisbane	0.906	39,296	35,614	Denver (0.659), Winnipeg (0.341)
Brussels	0.659	28,902	19,039	Copenhagen (0.378), Hong Kong (0.622)
Calgary	0.629	47,157	29,665	Copenhagen (0.871), Hong Kong (0.129)
Canberra	*1.000*	*45,010*	*45,010*	*Canberra (1.000)*
Edmonton	0.561	44,026	24,684	Copenhagen (0.644), Hong Kong (0.356)
Frankfurt	0.697	38,268	26,666	Copenhagen (0.630), Hong Kong (0.370)
Hamburg	0.407	36,744	14,949	Copenhagen (0.155), Hong Kong (0.845)
Melbourne	0.623	38,934	24,250	Copenhagen (0.778), Hong Kong (0.222)
Montreal	**0.859**	**77,788**	**66,851**	**Copenhagen (0.588), Hong Kong (0.412)**
Munich	0.797	18,195	14,508	Copenhagen (0.382), Hong Kong (0.618)
New York	0.467	51,655	24,142	Copenhagen (0.483), Hong Kong (0.517)
Ottawa	0.646	33,635	21,733	Copenhagen (0.520), Hong Kong (0.480)
Paris	0.666	24,255	16,151	Copenhagen (0.208), Hong Kong (0.792)
Perth	0.534	41,396	22,086	Copenhagen (0.831), Hong Kong (0.169)
San Francisco	0.418	65,806	27,488	Copenhagen (0.770), Hong Kong (0.230)
Sydney	0.508	35,053	17,822	Copenhagen (0.489), Hong Kong (0.511)
Tokyo	0.532	18,243	9,709	Copenhagen (0.077), Hong Kong (0.923)
Vancouver	0.471	37,146	17,508	Copenhagen (0.560), Hong Kong (0.440)
Vienna	0.557	20,616	11,486	Copenhagen (0.128), Hong Kong (0.872)
PT-oriented				
Copenhagen	*1.000*	*20,430*	*20,430*	*Copenhagen (1.000)*
Hong Kong	*1.000*	*9,605*	*9,605*	*Hong Kong (1.000)*
London	0.648	23,351	15,126	Copenhagen (0.281), Hong Kong (0.719)
Singapore	0.753	18,078	13,610	Copenhagen (0.316), Hong Kong (0.684)
Stockholm	0.873	26,835	23,420	Copenhagen (0.541), Hong Kong (0.459)
Toronto	0.576	33,573	19,330	Copenhagen (0.352), Hong Kong (0.648)
Zurich	0.666	25,230	16,816	Copenhagen (0.380), Hong Kong (0.620)

(continued)

Table 1.4 (continued)

City	EE score	Energy consumption (MJ/pkm)		Reference set (lambda)
		Observed	Optimum	
Developing				
Bangkok	0.490	29,959	14,684	Hong Kong (1.000)
Jakarta	1.256	9,072	11,397	Copenhagen (0.064), Hong Kong (0.936)
K.L.	0.525	20,003	10,497	Copenhagen (0.233), Hong Kong (0.767)
Manila	1.540	7,316	11,267	Copenhagen (0.141), Hong Kong (0.859)
Seoul	1.164	9,598	11,169	Copenhagen (0.214), Hong Kong (0.786)
Surabaya	1.286	5,606	7,212	Copenhagen (0.068), Hong Kong (0.932)

MJ megajoules, *pkm* passenger kilometers

improve its efficiency. Because the EE model proposed in this study allows cities to cross the borders of groups, such latent potential improvements in efficiency can be estimated. Furthermore, more feasible and practical solutions can be found by relaxing the constraints used to form the reference sets for each group.

1.5.2 Longitudinal Analysis

Cities can be classified into four cases based on the combination of the CU and FS indexes during the last four decades. For example, Case 1, where FS and CU indexes are higher than 1.0 shows the desirable growth of the entire global society, which implies that environmental technologies have been developed in frontier cities and that nonfrontier cities are attempting to catch up. Conversely, in Case 2, where the FS index is higher than 1.0 but the CU index is lower than 1.0, the consumption structure does not improve in nonfrontier cities, whereas it improves in relative terms in frontier cities. Therefore, the gap between frontier cities and the rest widens. In Case 3, where the FS index is lower than 1.0 but the CU index is higher, environmental technologies remain stagnant in frontier cities, and other cities attempt to catch up to frontier cities. Case 4, where both indexes are lower than 1.0, is the worst case, and environmental technologies remain stagnant in all cities.

Figure 1.14 shows the changes in the CU and FS indexes in all cities from 1960 to 1990. As a general trend from 1960 to 1990, each city makes a transition from Case 3 to Case 2. This trend shows that frontier cities have developed their environmental technologies. In particular, PT-oriented and compact cities (i.e., Copenhagen and Hong Kong) have an advantage. In contrast, PC-oriented and developing cities cannot catch up to frontier cities. In such cases, it would be effective to transfer policies that promote technologies from frontier cities in other cities. This may include the effective use of intellectual property rights that are not enforced, the effective use of human capital in personal exchanges, and the promotion of intercity coordination in joint research. In concrete terms, the policies in place in frontier cities in 1990 may

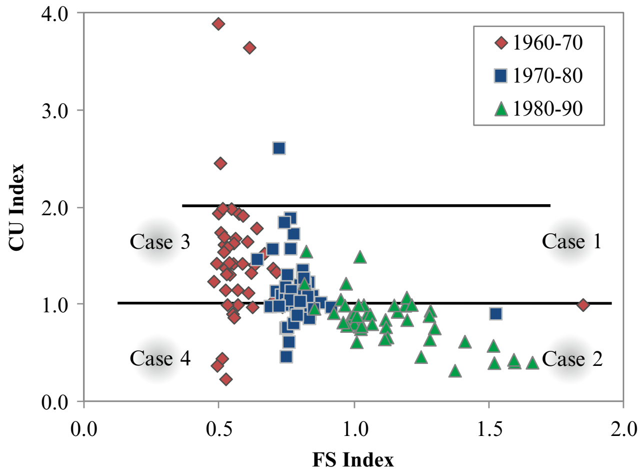


Fig. 1.14 Temporal change of environmental efficiency based on FS and CU indices

assist transport policy makers in other cities. For instance, in Copenhagen, the Finger Plan for transport-oriented development has been introduced (Nishi 2004). In addition, many transport policies are introduced in that plan; for instance, the regulation of loading ratios and the building of bicycle paths. Bicycle paths have also been built in Canberra. In other frontier cities, such as Hong Kong, a high-density PT network has been built. A PT network has been developed in Denver and Sacramento, and transit malls have also been introduced (Litman 2009). Such advanced policies may be useful in filling the gaps in environmental efficiency in other cities.

1.6 Conclusions and Future Research Issues

Sustainability has various dimensions and is affected by a range of factors. These dimensions and/or factors may vary according to stage of urban development. To capture the dynamic characteristics of sustainability comprehensively, theory-driven approaches such as the system approach are preferred. Such approaches usually need a large data set, which may be collected in developed countries; however, this is very difficult to do in developing countries. To support policy decisions in developing countries facing unprecedented challenges to become sustainable societies, some practical, cost-effective and easily measured indicators are needed. The first half of this chapter therefore focuses on developing such indicators at the city level based on a data-driven approach, considering the data availability in developing countries. From this, a dynamic structural equation model is established where dynamics are captured based on the concept of state dependence, and latent variables are used to derive the indicators of urban sustainability. It is confirmed that the structural equation model and data source provided by Kenworthy et al. (2000) can be used to derive the relevant sustainability indicators of urban development in developing countries. In particular, the proposed model explicitly takes into account the cause–effect relationships among the indicators over time. Such dynamic cause–effect relationships have been ignored in existing indicator frameworks. As for the policy aspects, it is found that transport supply policies supporting economic activities were the main factors determining energy consumption, while land-use policies played only a very limited role.

The latter half of this chapter proposed the EE model, based on the DEA cost-efficiency model, to estimate EE scores by evaluating the performance of the energy consumption structures of cities. The EE model was applied to assess the energy efficiency of transport systems in 46 developed and developing cities. The heterogeneity of structures in the cities' transport energy consumption was incorporated by relaxing the convex assumption across cluster groups. Consequently, heterogeneous cities with different characteristics in the same reference sets were not distinguished. Moreover, cities in neighboring clusters could not be used as a reference. Thus, the potential improvement of efficiency in a city could be estimated. This could not be done without the proposed EE model.

For empirical analysis, a panel analysis was conducted and showed that the gap in the quality of environmental technologies between frontier cities and others was a growing problem from 1960 to 1990. To solve this problem, it is important for frontier cities to transfer their advanced technology to other cities. The proposed approach can be used to seek the optimum emissions allowances by considering current energy consumption structures in corresponding cities and consequently could be useful in the establishment of more feasible and efficient targets in emissions trading schemes.

As for future research issues on the sustainability indicators of city development, the above-mentioned conclusions should be further examined based on more efficient estimation methods suitable for a small sample size. In addition, this study estimated the pooled model and dynamic model independently. These two models should be repeatedly estimated to obtain consistent parameter values. The convex relationship between economic activities and environmental emissions also needs to be reflected in the linear model structure; for example, by properly transforming the relevant variables. This analysis confirmed the effectiveness of the dynamic model for overcoming methodological shortcomings in existing indicator frameworks based on internal validity (goodness of fit). It is necessary to examine external validity; that is, temporal and spatial transferability. The question of how to represent the missing data as well as serial correlation and heterogeneity would also be an interesting research topic. Furthermore, evaluation of urban sustainability should not ignore social dimensions (e.g., equity). It seems worthwhile to evaluate the effects of policies contributing to sustainable urban development in developing cities.

With regard to environmental efficiency, the proposed model should be further improved in future research on policy evaluation. The efficiency scores obtained in this study may not always be accurate because of limitations in the available data and some strong assumptions. For instance, the efficiency score is calculated on the basis of only two factors: the use of private and public transport modes.

However, efficiency could result not only from the use of PT use but also from factors such as land use and urban structure. Therefore, the proposed approach should be expanded to more macroscopic analysis. Furthermore, although the cost variable was considered to be fixed in the EE model, the energy intensity of PT could change because of changes in transport distances. This assumption should be relaxed. In addition, improvements to the energy consumption database in both developed and developing countries are required. Policies such as those suggested in the "avoid, shift and improve" approach (GTZ 2009) should be urgently discussed to mitigate the effects of global warming.

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Chapter 2
Systematic and Behavior-Oriented Approaches for Sustainable Urban and Transport Policies

Junyi Zhang

Abstract To realize a sustainable urban and transportation society, good governance is required. This should be supported by systematic and scientific approaches that can generate informative indicators of factors such as policy evaluation, decision making, implementation, and monitoring. Urban and transportation systems are complex, and managing them needs interdisciplinary knowledge. Accordingly, this chapter argues for the importance of developing integrated urban and transportation models, and implementing interdisciplinary behavioral studies. The key point is to represent changes in the system and citizens' life behavior with regard to quality of life, environmental capacity and social equity. Both backcasting (top-down) and forecasting (bottom-up) approaches should be utilized, with sustainability transition emphasized as part of an interactive planning and policy-making scheme. Finally, context-sensitive urban designs should be promoted.

Keywords Behavioral change • Context-sensitive urban design • Cross-sectoral policies • Integrated models • QOL • Sustainability transition • Systematic approach

2.1 Background

In the year 1800, only 2 % of the world's population was urbanized, but in 1950, 30 % of the world's population lived in cities (UNHSP/BASICS1/02). Currently, for the first time in history, more people now live in urban than in rural areas (The United Nations 2011). It is estimated that half of the population of Asia will live in cities by 2020, Africa will probably reach a 50 % urbanization rate in 2035,

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and this growth in urbanization will be unequally distributed, mostly in the developing world: Asia, Africa and Latin America (The United Nations 2012).

The above rapid urbanization has resulted in an exponential growth in mobility, which has contributed to great social and economic advances on the one hand but has caused various problems (e.g., traffic congestion, declines in road safety, excessive energy consumption, air pollution and the resulting worsened health conditions) on the other. Especially in developing countries, such issues are serious and complicated because of the extreme lack of urban infrastructure, poor construction and maintenance of facilities, and disorderly urban land development. There is also high dependence on ill-equipped paratransit systems (e.g., jeepneys, tricycles, tuk-tuks, soibikes, pedicabs, rickshaws and dilimans), poverty and lack of governance (e.g., lack of funding, insufficient laws and regulations, lack of qualified people, and low levels of technological development). Comparing developing with developed countries, one can easily observe similarities in the growth process because developing countries attempt to catch up with developed countries by imitating their development patterns. However, increasing concerns about environmental issues around the globe give rise to dissimilarity. In the past, when developed countries were in situations similar to those in developing countries now, they did not have to pay so much attention to environmental issues because economic growth was the highest priority among policy objectives. Currently, policy makers in developing countries face increasing constraints, such as monetary and technological limitations, lack of qualified human resources or collaboration among actors (such as government, firms and citizens), and the resultant worsened social capacity for environmental management (Zhang et al. 2005; Zhang and Fujiwara 2006a, 2007). Although developing countries are currently not major contributors to environmental burdens, challenges in developing countries will have worldwide implications.

Developing cities in a more sustainable way is therefore of increasing importance. As Bossel (1999) argues, the sustainable development of human society has environmental, material, ecological, social, economic, legal, cultural, political and psychological dimensions that require attention. Some forms of sustainable development can be expected to be much more acceptable to people. In the context of urban transportation system, UITP (2003) advocates that sustainable transportation is an aspect of global sustainability that involves meeting present needs without reducing the ability of future generation to meet theirs. A sustainable transportation system should meet the basic access needs of individuals and societies, be affordable, operate efficiently, and limit its emissions and waste to remain within the planet's ability to absorb them.

2.2 Importance of Systematic Thinking

To meet various human needs for urban spaces/functions and at the same time to mitigate the impact of human activities on the environment, urban systems must be appropriately designed. There is no doubt that investment in urban infrastructure (e.g., roads, transit systems, sewerage and water systems, urban amenities, community and cultural facilities) plays a key role. Because improvement in urban infrastructure is usually large scale and extremely expensive, such investments must be as efficient and cost-effective as possible. Meanwhile, to reduce environmental emissions, our whole society must make various practical efforts by fully utilizing available capital assets (including natural, physical, financial, human and social capital) with good collaboration of various stakeholders including government, firms and civil society. Government and firms are required to guide people toward living in a low-carbon society; however, they may fail because of their "soft heartedness" toward citizens/consumers. In case both market and government failures occur, citizens must protect themselves. For example, they may need to reconsider their energy-intensive lifestyles, to be more cost sensitive and altruistic, and to make more proenvironmental choices of goods/services, and they may be required to share responsibility. To realize a socially acceptable sustainable urban and transportation society, it is becoming extremely important to improve understanding of citizen and consumer behaviors. Note that sustainability cannot be realized in an instant. Emphasis must be placed on the "sustainability transition" (Expert Group on the Urban Environment 1996). In other words, the way to move from the current unsustainable state to a future sustainable state should be emphasized.

To tackle the unsustainable urban and transportation issues, it has been argued that various policies should be packaged (e.g., Institute of Highways and Transportation 1996). These policies may include the following:

- Integrated land-use and transportation planning,
- Anti-car measures (e.g., control of car ownership and use, road pricing, enforcement of illegal parking),
- Transit-friendly measures (e.g., prioritizing transit systems, providing information, IC cards and fare systems),
- Pedestrian- and bicycle-friendly measures (e.g., traffic calming, providing pedestrian/bicycle spaces and open spaces),
- Improving road networks (e.g., creating arterial road networks, reallocating road space, implementing environmental measures at the roadside, and providing parking spaces),
- Universal design for transportation-poor people,
- New technologies (e.g., ITS (intelligent transport systems) and low-emission vehicles), and
- Policies to support voluntary changes in behavior.

To date, various planning theories have been developed and applied in practice, including system and rationalism theories, Marxist theory, advocacy planning theory, new right urban planning, pragmatism and post-pragmatism theory, post-modern planning theory, and interactive planning theory (American Planning Association 2006). In recent years, the interactive planning theory has increased in popularity because of its theoretical features, in that it attempts to realize consensus building based on dialogue in the ideal public situation where no external pressure is imposed and workshop and round-table approaches are usually adopted. In reality, however, it is difficult to prepare an ideal planning situation. Policy makers are required to solve issues arising from complexity, various constraints and diverse values. To support such difficult decisions, systematic thinking is especially important. Policies need to be properly evaluated to build consensus among the public before implementing them. Policies should be evaluated by addressing the following concerns (Hanley and Spash 2003):

- Appropriateness (e.g., what information on impacts and trade-offs is required for the decisions?),
- Equity (e.g., what is the distribution of benefits and costs among members of the community?),
- Effectiveness (e.g., is the alternative likely to produce the desired results?),
- Adequacy (e.g., does the alternative correspond to the scale of the problem and to the level of expectation of problem solution?),
- Efficiency (e.g., does the alternative provide sufficient benefits to justify the costs?),
- Implementation feasibility (e.g., availability of funds, administrative or legal barriers, organizational capability, public acceptance), and
- Sensitivity analysis (e.g., sensitivity of analysis results to the change of assumptions made, and the likelihood of these changes occurring).

Approaches to support the complicated and difficult policy decisions above usually include the following:

1. The rational actor approach in which alternatives are selected to obtain a set of predetermined goals and objectives that maximizes utility;
2. The satisfying approach in which the first alternative that meets the minimal level of acceptability is selected;
3. The incremental approach in which decision making is geared toward avoiding problems rather than attaining objectives;
4. The organizational process approach in which decisions are highly influenced by organizational structures, channels of communication, and standard operating procedures, and
5. The political bargaining approach in which the decision process is pluralistic and characterized by conflict and bargaining.

The above-mentioned methods and theories are usually applied independently or jointly depending on context, issues and countries. Applying these methods/theories also requires the consideration of steps throughout the policy-making process, which are usually: identifying issues; setting goals, objectives and priorities; collecting and analyzing data; generating alternatives; predicting future evaluations; making decisions about planning; implementing the planning, management and maintenance processes; monitoring; and recommencing the process. Nevertheless, in practice, the monitoring step in particular is usually ignored because it requires continuous monitoring. Monitoring progress of policies is itself a public expense and therefore has an opportunity cost (Maxwell and Conway 2000), which in many cases becomes a barrier to its implementation.

2.3 Methods of Building Integrated Models

The development of integrated models has been popular in the context of land-use and transportation systems, which are usually interdependent of each other (Timmermans 2003; Wegener 2005; Miller 2006). Land-use patterns influence choice of residential and work location as well as the locations of activity facilities. Consequently, they affect a series of decisions regarding trips, such as whether to take a trip (trip generation), how frequently trips are taken (trip frequency), where to go (destination choice), how to travel (travel mode choice), when to go (departure time choice), and which route to take (route choice). Conversely, a transportation system also generates a variety of outputs such as travel time, cost, emissions and noise, which determine factors such as the accessibility of places connected to the transport system, quality of life/work, and activity facility environment. Accessibility and quality of environment significantly influence land price, which is the most important determinant of supply in a land-use system. It should be noted that relationships between land use and transportation are usually cyclic and change over time (Giuliano 1989).

There are a number of integrated land-use transport systems that are in use today, such as ITLUP, EMPAL, DRAM, METROPILUS, MEPLAN, TRANUS, RURBAN, and UrbanSim. There are significant variations among these models with respect to overall model structure, comprehensiveness, theoretical foundations, modeling techniques, dynamics, data requirements and model calibration. Detailed reviews are given by Wegener and Fürst (1999), Timmermans (2003), Wegener (2005) and Miller (2006). To date, the integrated models above have mainly been applied in North American and European cities (Wegener 2005). There are only limited applications in developing countries (e.g., Ratchapolsitte et al. 1986; Udomsri 1993; Emberger et al. 2005; Vichiensan and Miyamoto 2005). The lack of application in developing countries may be because of the data requirements for integrated models, lack of consideration of behavioral mechanisms specific to developing countries in the models, and lack of human resources.

One of the most prominent characteristics of developing countries is the enormous growth of their urban areas (Echenique 1986). Because the pace of development is very rapid in urban areas, it becomes very difficult to deal with problems of urbanization in developing countries. This leaves many suburban areas with inadequate supplies of urban infrastructure such as water, sewerage and transportation. In addition, many policies adopted to cope with urbanization problems in the developing world have become insufficient and have imposed high financial costs on society (Echenique 1986). Thus, an integrated model for developing countries should capture the development dynamics properly and should locate the various well-defined and realistic public policies appropriately. Moreover, the model should be sufficiently flexible to use available data, which is the main source of bottlenecks in developing a comprehensive integrated urban model in developing country contexts.

Bearing in mind the above-mentioned difficulties in the context of developing countries, some issues related to the development of integrated urban models are discussed below from the perspectives of population and economic activities, land use, location choice, transportation, and policies. Developing countries are characterized by rapid population increase as well as high levels of migration to urban areas. On the other hand, formal economic activities often fail to attract an adequate supply of labor in urban areas. The immediate solution to this inadequacy is supplied by informal sectors of the economy, which are rarely seen in developed economies. In the informal sectors, workers often are not registered properly and are paid on an informal basis to avoid the required payments for government social security and welfare services. Population and workforce development in urban areas is conditioned on very diverse dynamics such as population increases in other urban areas and surrounding rural areas. Thus, increases in the population in both urban and rural areas, and development of general economic activities should be modeled separately. As indicated above, population increases are very rapid in developing countries, and economic activities are very diverse. Accordingly, changes in land use also occur very fast. Changes in both resident population and economic activities occur in both formal and informal ways in developing countries, such as in slum housing and industrial areas. Such rapid changes in land-use patterns should be properly represented. Furthermore, location is chosen during the development of land use. In this regard, population increases and economic activities should be disaggregated into households and individual businesses, which are expected to choose among the available land uses. Heterogeneity in location choice decisions cannot be ignored. With regard to transportation, at least, trip generation, distribution, and modal splits should be built as dynamic models, such as in the manner suggested by Sugie et al. (2001), who built a dynamic travel demand model with state dependence, serial correlation and heterogeneity at the aggregate level based on a person's trip data with three time points. At the same time, because paratransit (an informal transport mode) in developing countries plays dual roles, such as providing convenient and flexible transport services, and providing employment opportunities to low-income people, it must be properly represented in the integrated model to clarify its position in future transportation systems from the perspectives of not only transportation services but also social equity.

All public policies should aim to improve people's quality of life (QOL). Implementation of policies cannot have an impact on nature that exceeds its carrying capacity. In the case of urban and transportation development, as UITP (2003) argues, sustainable transportation systems are required to balance economic development, environmental emission and social equity. In this case, sustainability becomes the policy goal. Specifically, in the economic field, accessibility and mobility should be maximized; in the environmental field, emissions from transportation systems should be minimized, and in the social field, equity in accessibility and mobility should be maximized. Obviously, these sustainability goals must be realized with consideration for various uncertainties and constraints. Examples of such constraints could be civil minimum standards of accessibility and mobility, environmental standards and limits (i.e., capacity), technological and institutional constraints, and public acceptance. From this viewpoint, the integrated models reviewed above can be called "bottom-up" approaches in the sense that the models are based on past and present information without incorporating any policy goals. Bottom-up approaches are usually used to identify potential policies based on scenario analysis, whereby detailed policy goals are not defined in advance, and forecasting is therefore required. On the other hand, because of the difficulties of following the demand trend in resolving various transportation issues, target-based planning and policy decisions have recently grown in popularity, especially in the design of a low-carbon society. For such planning and policy decisions, top-down modeling approaches enhanced by the incorporation of backcasting techniques are required. Target-based planning is proposed, reflecting the facts that reality is complex and that information is imperfect, and the need for planning to be sufficiently flexible to account for, and adapt to, changing circumstances (Maxwell and Conway 2000). Planning needs to move from a blueprint to a process approach, and targets can be used to monitor the progress of policy. In essence, developing a top-down modeling approach is a multiobjective optimization problem (such as those approached with the bi-level programming (BLP) method) because it must consider not only future targets but also current system performance as well as various constraints.

As the Expert Group on the Urban Environment (1996) argued, the "sustainability transition" should be emphasized over the final goals of sustainability. For this purpose, as well as to enhance the public acceptance of policies, bottom-up approaches and top-down approaches may be combined in a hybrid approach to achieve policy goals and to monitor the progress of policy implementation. One critical difference between top-down and bottom-up approaches is that constraints in policy implementation are explicitly reflected in the modeling process of top-down approaches. In contrast, constraints are usually considered in examining the feasibility of policy scenarios identified after the model construction. A conceptual illustration of this hybrid modeling process is shown in Fig. 2.1 and briefly discussed below.

Policy goals: In the top-down approaches, policy goals with detailed targets (e.g., reducing CO_2 emissions in 2050 by 50 %) are predefined. To achieve policy targets, the best policy set is identified. On the other hand, in the bottom-up approaches, policy scenarios are first proposed and the effects of each scenario are evaluated; based on the scenario analysis results, better policy sets are determined. The experience of developed countries suggests that in the era when infrastructure construction was the focus in policy agenda, they mainly adopted top-down approaches. With the progress of urban development, circumstances surrounding policy decisions changed dramatically, and goal setting itself has become increasingly difficult. Now, partially because citizen participation has become more popular, bottom-up approaches are widely applied. Meanwhile, issues such as global warming have attracted greater attention from various stakeholders, including governments, firms and civil society. To respond to such new policy requirements, top-down approaches with clear targets are gaining in popularity. To realize policy goals specified in the top-down approaches, citizen participation is obviously required, especially in the stage of policy implementation.

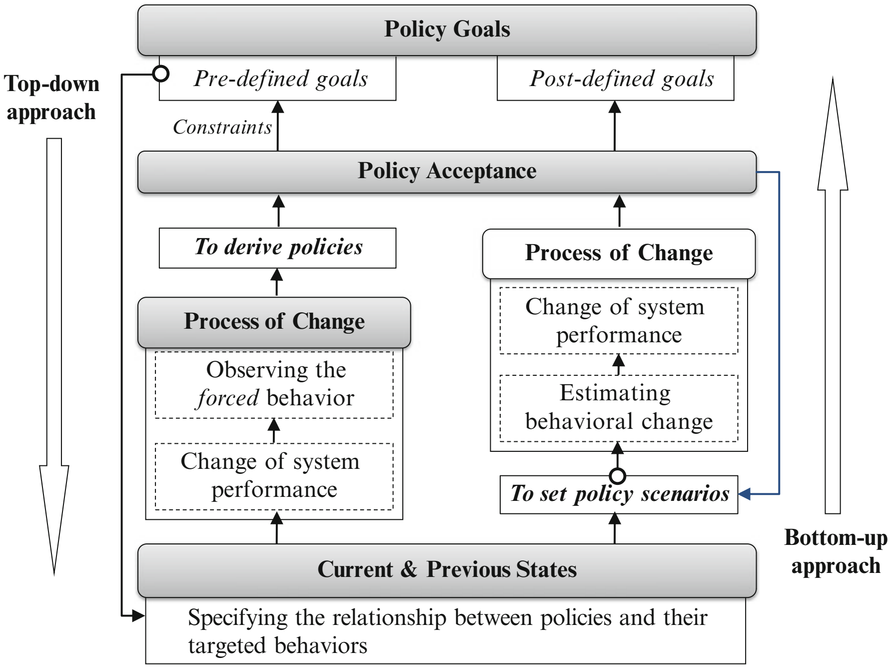

Fig. 2.1 Conceptual illustration of hybrid-type integrated models

Current and previous states: To build any type of models, it is necessary to understand current and previous states to clarify the relationships between policies and targeted behaviors/systems. Various types of surveys have been used to provide well-grounded insights for urban and transportation policy decisions. Of course, reliable survey data are essential to support better policy decisions. To date, travel diary surveys, activity diary surveys, panel surveys and stated preference surveys (e.g., Richardson et al. 1995; Stopher and Jones 2003) have been developed to improve understanding of activity and travel behavior for various policy purposes. On the other hand, it is known that activity and travel behavior changes according to time and context. Temporal changes also show variation in time scales (e.g., hour-to-hour, day-to-day, week-to-week, season-to-season, and/or year-to-year variations). To capture such changes, panel surveys could and should be used (e.g., Golob et al. 1997; Stopher 2009); however, in reality, their application is very limited for various reasons, one of which is that they are time-consuming and too costly. As a result, in practice, transportation surveys are usually conducted by focusing on a representative (or an average) day (at most several days), and the survey results are then used to predict long-term and/or short-term travel demand. Moreover, it is difficult to apply existing survey methods to capture the influence of different contexts, which can be classified into individual-specific, alternative-specific, and circumstantial contexts (Zhang et al. 2004b). The first type refers to the attributes of individuals and their households. The second indicates the context of availability, number and attributes of alternatives as well as the associated correlation structures. The last type refers to circumstantial factors (e.g., weather, economic conditions, and city characteristics), which are common to all decision makers. In theory, it is obvious that information collected on one or several days cannot be used to capture fully the temporal and contextual variations in behavior of the whole population. Interestingly, several so-called "continuous" surveys have been conducted around the world at the national, regional and metropolitan levels. In these surveys, "data for each respondent are sought for the 24 h of the day in the seven days of the week and in all seasons of the year; further, the effort should be kept going for several years" (de Ortúzar et al. 2011). Therefore, it is extremely important to capture the past and current states properly based on continuous rather than cross-sectional surveys (i.e., surveys are conducted at a specific point in time).

Process of change: This term refers to changes in system performance as well as users' behavioral changes. In practice, monitoring of policies has been ignored because of factors such as political pressures and budget constraints. In fact, policies identified during the decision-making process are made based on assumptions. Because information about the future is insufficient and uncertain, the expected effects of policies may not be realized. For this reason, it is extremely important to monitor the actual effects of policies. If the effects are too far from, or in conflict with, the goals, redesign of policies is required. In the top-down approaches, changes in system performance are required to meet policy goals. To achieve these changes, users should be effectively encouraged to change their behavior. In the bottom-up approaches, changes in users' behavior in each scenario are estimated, and based on these estimates and changes in system inventories (supply), change in system performance is calculated. It may be seen that in either case, change in user behavior is the core of the analysis. To date, supply-centric policies have dominated the practice. In reality, traffic congestion is still serious, and the resulting air pollution remains problematic. All these facts suggest that supply-centric approaches alone cannot resolve various transportation-related issues. Considering the limitations of supply-centric approaches, demand-centric approaches should be emphasized. Practical policy decisions have only scratched the surface of users' decisions about their behavior.

2.4 Importance of Behavior Studies

Increasing traffic capacity by constructing new roads has been observed to be ineffective in reducing traffic congestion and resolving associated issues. Recently, recognizing the limitations of supply-oriented policies in resolving transportation issues, a new approach, known as the A–S–I (A: Avoid/Reduce, S: Shift/ Maintain, I: Improve) approach, was proposed to reduce GHG emissions, energy consumption and congestion, with the final objective of creating more livable cities (www.sutp.org). The ASI approach aims to mitigate the impacts of transportation activities.

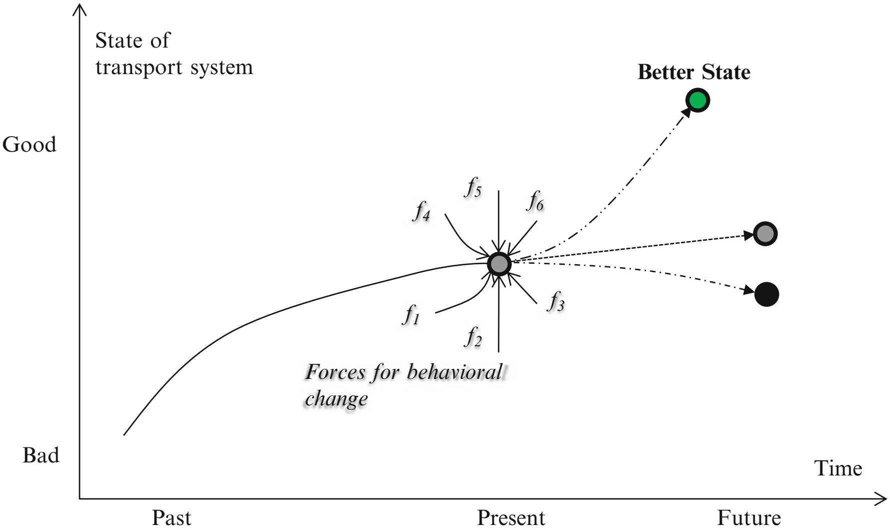

Fig. 2.2 Forces for behavioral change and transport policy decisions

Because of climate change, as GTZ (2009) argues, transportation systems will confront more extreme weather conditions if no adaptive measures are taken. More frequent disruptions and higher economic costs must be expected, so adaptation measures are required. It is further argued that a resilient transport system is the backbone of a sustainable urban system and is necessary to avoid large and costly disruptions to urban life.

Generally, transport policies are intended to transform currently undesirable transport systems into better ones. The problem is whether and how users of transport systems follow the proposed policies or planning. Therefore, to support transport policy and planning decisions, it is essential to understand and measure the behavior of users properly. This study only focuses on travelers (i.e., passengers), and attempts to propose better methods to measure travelers' responses to policies or planning. As shown in Fig. 2.2, various forces can result in behavioral changes; some improve behavior, such as f_1 and f_2, while others, such as f_4–f_6, play the opposite role. Different forces could act on behaviors in either a linear or a nonlinear way. It is expected that travelers might respond differently even to the same force, and such responses may change over time and from context to context. Thus, it becomes important for policy decision makers to capture travelers' responses to policies in a proper manner. In other words, transportation planners need to understand people's responses when introducing new policies. However, people's responses to a policy usually differ among population groups and in most cases are not transferable across space and over time. This means that analysis results obtained from one city cannot be applied directly to other cities, suggesting that it is important to implement relevant surveys to investigate behavior and/or attitudes, and/or to develop models to represent/predict behavior/attitudes.

2.5 Travel Behavior Theory

2.5.1 General Features of Travel Behavior

Travel behavior theory is a discipline about how people make a trip across space and over time, and how people use different transport modes and so on. Decisions usually include trip frequency (how many trips do people take in a given time period (e.g., a day)?), activity choice (what kinds of activities do people participate in after the trip?), destination choice (where do they go?), travel mode choice (which travel mode do they take?), departure time choice (when is the trip taken?), and route choice (which route do people choose for a trip?). Travel behavior theory helps transportation researchers and policy makers to understand travel choices and the conditions that encourage people to change their travel behavior. To change travel behavior, for example, measures include:

1. Increasing the cost and difficulty of private car use (e.g., increase gasoline taxes, introduce a congestion charge),
2. Making public transport more attractive by providing cheaper and more frequent transport,
3. Managing mobility (e.g., change user attitudes by emphasizing the socioenvironmental cost of private vehicle use using effective communication), and
4. Providing information (most travel information is currently supplied to road users, but similar information should also be provided to users of public transport systems).

Trip generation: This refers to the decision of whether to stay at home or to participate in out-of-home activities. Understanding trip generation is essential to identifying the total amount of trips per day, which determines the magnitude of impact of travel on human lifestyles, ecosystems, and sustainable development. Reducing the total number of trips generated may be the most effective way to reduce the environmental impacts of travel. Because of capability constraints, some people may have few chances to take trips for out-of-home activities. Efforts to address such social inequity would require focus on decisions concerning trip generation.

Activity choice (Trip purpose): Generally, a trip can be taken for one or more purposes, such as commuting, shopping, and recreation. Trip purpose corresponds to choice concerning types of activities. Trip purpose is closely related to the flexibility of trip scheduling and consequently determines the possibility of reducing/modifying a particular trip for environmental purposes. Activity decisions have several important policy implications. First, if some activities can occur at home rather than outside, then some trips can be avoided. Second, activity decisions include time use (e.g., number of activities, duration and timing, sequence and activity patterns), which are closely linked with people's QOL. Third, if several activities can be performed in the same place, this can also reduce traffic loads. In other words, if urban space allows people to perform various activities within a small space (a compact city), not only can traffic demand (especially longer intracity trips) be reduced but also

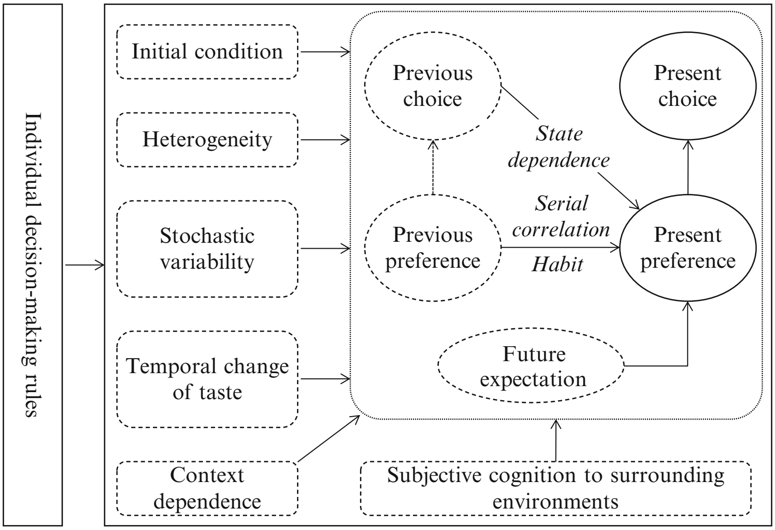

Fig. 2.3 A general dynamic choice model structure

economic activities can be performed more efficiently, and social communication can be promoted.

Destination choice: This refers to where a trip goes; that is, the choice of place. Examples include workplace, city center and shopping centers in the suburbs. A traveler can perform one or more activities in a single place. Understanding choice of a destination or place is essential for promoting the development of compact cities and other environmentally friendly urban forms.

Departure time choice: This indicates when a person leaves from a point of origin (e.g., home or workplace). Understanding departure time choice behavior is especially useful for daily travel demand management. Comparison of the above travel choice aspects suggests that it is much easier and more practical (acceptable) to shift peak travel demand to off-peak periods.

Travel mode choice and route choice: These indicate type(s) of travel mode(s) (e.g., car, bus, railway, motorcycle, bicycle, and walk) and route(s) (e.g., toll road or nontoll road) chosen. To reduce environmental load from travel, it is necessary to promote the use of public transportation and bicycling/walking. It is useful to encourage those who must use their cars to use less-congested roads.

Obviously, some of the above behaviors are decided independently, while others may be connected. It is also expected that travelers' responses to transport policies may differ across the above behaviors. Ideally, they should be modeled together. However, it is difficult to include all these decisions in a single thesis. Therefore, this study only deals with some travel decisions, as clarified below. As for the behavioral mechanisms in travel decisions, a general dynamic choice model structure is given in Fig. 2.3, summarized by Zhang et al. (2004a). Specifically, current choice behavior is determined by individual preference, which is influenced by previous preferences (i.e., habit) and results of previous choices (i.e., state dependence) and sometimes by future expected behavior (or future expectation). Such behavioral mechanisms are further affected by initial conditions, heterogeneity in personal tastes over time, context dependence, and stochastic variability. It is expected that individuals' subjective recognition of the environments in which their decisions are made may also influence the above behavioral mechanisms, which are governed by individual decision-making rules. When these rules change, all the above mechanisms may also change to some extent.

2.5.2 Typical Travel Behavior Models

Over the past four decades, choice models have been widely applied to analyze and predict decision makers' choices of one of a finite set of mutually exclusive and collectively exhaustive alternatives. Choice models have proved to be very powerful tools for forecasting changes in people's choices according to demographics and/or attributes of the alternatives. The multinomial logit (MNL) model has become the most widely used choice model in transportation, probably owing to its simple mathematical structure and ease of estimation. Because it assumes that the error terms of the utility function are independently and identically distributed across alternatives, the MNL model is characterized by the Independence of Irrelevant Alternatives (IIA) property, which states that the odds of choosing a particular alternative are independent of the existence and attributes of any other choice alternative in one's choice set. Convincing examples have been put forward, however, to show that this property of the MNL model is counterintuitive in many real choice situations. To resolve the above issue, the development of non-IIA choice models has become a major methodological challenge in the study of individual choice behavior in many disciplines since the late 1970s. In transportation research, interest in developing non-IIA models seems to have faded slightly as a result of the emerging field of activity-based models of travel demand, but recently a renewed interest has been apparent (see Zhang et al. 2004b for an example). The majority of non-IIA models introduced in the transportation research literature avoid the IIA property by allowing for covariance between the error terms of the utility functions for all or bundles of choice alternatives in a choice set.

Following the classification by Timmermans and Golledge (1990), Zhang et al. (2004b) presented an extensive review of choice models in transportation and relevant fields at the time of writing, focusing on three categories of choice models. The first group of non-IIA models avoids the IIA property by relaxing the assumption of identically and independently distributed error terms, allowing for different variances of error terms, for positive correlations between error terms, or for both. The second group of non-IIA models circumvents the IIA property by extending the utility specification to account explicitly for similarity between choice alternatives. In other words, the models suggest that individual choice behavior is context dependent. The third group of non-IIA models assumes a hierarchical or sequential decision-making process.

Examples of the first group include McFadden's (1978) generalized extreme value (GEV) model, Hausman and Wise's (1978) conditional probit model, the multinomial probit model (Daganzo 1979), the heteroscedastic extreme value model (Bhat 1995), and the mixed logit/probit model (Brownstone et al. 2000).

For the second group, Swait and Adamowicz (2001a) proposed a latent class model of decision strategy switching to represent the influence of task complexity on consumer choice. Swait and Adamowicz (2001b) developed a theoretical model that simultaneously considers task complexity, the amount of effort applied by the consumer, ability to choose, and choice. Oppewal and Timmermans (1991) applied a mother logit model (McFadden et al. 1977) to estimate context effects in the choice of housing, shopping centers and transportation modes. Anderson et al. (1992) developed a similar model to represent attribute cross-effects and availability cross-effects in a study of mode choice. Gaudry and Dagenais (1979) proposed a dogit model to avoid the IIA property by introducing nonnegative alternative-specific parameters to represent substitution (similarity) effects. Borgers and Timmermans (1988) developed a context-sensitive model of spatial choice behavior to capture substitution/similarity effects as well as spatial structure effects.

The best-known model with a hierarchical decision structure is the NL model (Ben-Akiva and Lerman 1987), which is a special case of McFadden's GEV model. Other types of such models have also been derived from the GEV model, including the PCL, CNL, OGEV, PD and GNL models (Wen and Koppelman 2001). Recently, a nested PCL (NPCL) model was developed by Fujiwara and Zhang (2005). The GNL model in particular can include the above-mentioned models and the MNL model as special cases and closely approximates the NL model. A completely different approach is Tversky's (1972) elimination by aspects model. This model is one of the noncompensatory models. Most of the models described in this section assume that choice behavior is compensatory. These models allow a low score on an attribute to be at least partially compensated by high scores on one or more remaining attributes. In contrast, noncompensatory models assume that individuals screen choice alternatives on an attribute-by-attribute basis when arriving at a choice.

2.5.3 Important Decision-Making Mechanisms

Careful review of travel behavior models suggests that the following behavioral mechanisms are important in travel decisions: heterogeneous dynamics, similarities in bundle choice behavior, reference dependence, and group decision-making mechanisms.

2.5.3.1 Heterogeneous Dynamics

Heterogeneous dynamics indicate that choice behavior changes over time (i.e., temporal change) and that such changes differ across individuals (Zhang et al. 2004a).

1. *Temporal Behavioral Changes*
   Temporal changes can be classified based on the time interval, such as real-time change, change between peak and off-peak hours, day-to-day, week-to-week, season-to-season, and year-to-year changes. Some changes may recur periodically, while others may recur at a certain rate over time (or change at a regular rate). Because choice behavior is highly adaptive and context dependent (McFadden 2001), changes to decision contexts over time may result in changes in behavior. Changes of factors affecting travel behavior over time may also lead to a change in behavior, such as travelers' attributes (e.g., age, employment, family structure, habits, attitudes, and motivations), factors of choice alternatives (e.g., travel time and cost, and trip purpose), and circumstantial factors (e.g., weather, economic situation, car ownership among the population, and policies of road pricing for road users).

   To capture these behavioral changes, it is first useful to introduce the above factors into travel behavior models or to build dynamic behavior models. The development of disaggregate dynamic travel behavior models has been pursued since the 1980s. Heckman (1981) proposed a typical dynamic discrete choice model in which true state dependence, cumulative effects and behavior inertia are jointly accommodated. Recently, in line with Heckman's model, Swait et al. (2004) derived a new dynamic model derived from the well-known GEV model family (McFadden 1978), into which initial conditions, future behavior expectations, state dependence, the scale parameter of time-variant taste, covariance structure and preference can be simultaneously incorporated.
2. *Heterogeneity*
   Heterogeneity can be caused not only by the observed characteristics of individuals (e.g., gender, age, income, and number of households) but also by unobserved characteristics (e.g., omitted variables of the preference, attitudes and motives) (Reader 1993; Sugie et al. 1995, 1996; Swait and Bernardino 2000; Zhang et al. 2001). The former is called observed heterogeneity and the latter unobserved heterogeneity.

   Observed heterogeneity can be captured using market-segmentation techniques (e.g., Tynan and Drayton 1987; Morikawa and Shiromizu 1991). In the marketing research field, various scanner panel data are available. Such panel data can be used to explore the observed heterogeneity of each individual consumer directly (Terui and Dahana 2006). In the transport sector, various IC cards have been widely introduced (Bagchi and White 2005). The rapid progress of such information and communication technologies makes the direct observation of human behavior over time and across space easier. Although the privacy issue cannot be ignored, a new way of directly observing behavioral changes is surely opened.

   Unobserved heterogeneity can be observed in many components of choice models, including taste for alternatives, taste for attributes, error structure, state dependence, initial conditions in panel analysis, choice set, and model structure.

   Taste for alternatives: This is described as a form of "alternative-specific constant term." When it does not follow a probability distribution—that is, it is assumed to be invariant over the population—the choice model is called a "fixed-effect model." In contrast, when it follows a distribution, it is called a "random-effect model," which further consists of parametric and nonparametric models (Chamberlain 1980; Reader 1993; Sugie et al. 1995, 1996; Zhang et al. 2001; Heckman and Singer 1984).

Taste for attributes: Attributes can be alternative-specific and/or alternative-generic. It is usually assumed that taste parameters follow a multivariate normal distribution. Mixed logit and mixed probit models are the two main types of models (Bhat 2001; Bhat and Guo 2004; Revelt and Train 1998; Brownstone et al. 2000; Rossi et al. 1996; Hensher and Greene 2003).

Error structure: Bhat (1997) defined the parameters of a logsum variable in a nested logit model as a function of individual attributes to represent the error covariance structure with heterogeneity and applied it to the analysis of intercity transportation. Recently, multilevel modeling approaches have become a more general method for capturing heterogeneous error structures by dividing the error terms into different unobserved stochastic components (e.g., Chikaraishi et al. 2009, 2010).

State dependence: Bhat and Castelar (2002) analyzed a congestion pricing policy using a mixed logit model by including three kinds of heterogeneity (preference, state dependence and the preference for LOS variables) in a combined RP/SP model.

Initial condition: This is a special behavioral phenomenon in the panel analysis. Two typical methods were proposed to represent its heterogeneity—the fixed initial condition method and the correlating initial condition method—where the former disregards the influence of unobservable heterogeneity, while the latter takes it into account (Heckman 1981).

Choices set: Chiang et al. (1999) proposed a model to describe jointly the heterogeneity of a choice set and that of preference parameters. As for preferences, it is assumed that the parameter follows a normal probability distribution.

Model structure: In discrete choice behavior, Wu et al. (2011), for example, developed a heterogeneous choice model of destination and travel parties by combining a nested logit model and a latent class model. Using the same latent class model, Kuwano et al. (2007) developed a household vehicle holding duration model for continuous choice behavior. Walker and Ben-Akiva (2002) proposed a generalized random utility model that can comprehensively represent the error structure, latent classes, latent variables, and heterogeneity of SP and RP data.

2.5.3.2 Similarities in Bundle Choice Behavior

It is not unusual that consumers choose a set of alternatives (i.e., a bundle alternative) in a single purchase situation. Targeting such consumer behavior, firms often sell their goods in packages: sporting and cultural organizations offer season tickets, banks offer checking, safe deposit, and travelers' check services for a single fee (Adams and Yellen 1976). In economics, such sales of packages are called "commodity bundling." In fact, travelers also often make a joint choice of two or more travel decisions, such as travel mode and departure time, or destination, travel mode and route. In other words, travelers choose a combination of two or more travel elements. This is an example of bundle choice in transportation.

In marketing research, bundle choice is classified as a part of multiple-category choice. Conceptually, a multiple-category choice can be defined as a decision process in which the choice of one product or brand is affected by the presence of another product in a different category, and there are a variety of ways in which choices across different product categories may be linked (Russell et al. 1999). Bodapati (1996) uses a nested logit framework to represent bundle choices. Manchanda et al. (1999) use a multivariate probit (MVP) model to reveal how marketing activity in one product category influences purchase incidence decisions in another category. In addition, market basket analysis is an attractive approach to studying the composition of a basket (or bundle) of products purchased by a household on a single shopping occasion (Russell et al. 1997).

Related to the above bundle choice, Zhang et al. (2004b) develop a relative utility model in the context of transportation. The concept of relative utility assumes that utility is meaningful only relative to some reference point(s). It is argued that an individual evaluates an alternative by comparing it with other alternatives, or perhaps with the alternatives previously chosen by the individual, or with those chosen by other individuals. The form of the relative utility function shows that the relative utility of an alternative is defined as a special case by reflecting the influences of other alternatives in the choice set. Thus it is expected that relative utility can be used to represent cross-category choice dependence. Compared with existing cross-category modeling approaches, the relative utility model can be estimated much more easily using the standard maximum likelihood estimation method, without the difficult hierarchical Bayesian estimation technique.

2.5.3.3 Reference Dependence

From a psychological viewpoint, choice behavior is highly adaptive and context dependent (Tversky and Simonson 1993; McFadden 2001). Kahneman and Tversky (1979) argue that choice behavior depends on status quo or reference point and that a change of reference point may lead to preference reversal. Considering that the development of travel behavior models was intended to support policy decisions, it is important to define context dependence properly to avoid seriously biased inferences. For this reason, Zhang et al. (2004b) reclassify context into alternative-specific, circumstantial, and individual-specific contexts, and formulate a relative utility model that uses these reference points as anchor points. Conceptually, it is assumed that an individual evaluates an alternative in a choice set in comparison with other alternatives (alternative-oriented relative utility), with the alternatives that the individual has chosen in the past (or possibly the future) (time-oriented relative utility), or with the alternatives chosen by other individuals (individual (or decision-maker)-oriented relative utility). Circumstantial context further suggests that such decision-making mechanisms vary with contextual factors (e.g., weather and economic situation), which are common to all individuals (decision makers).

As a theory of decision making under uncertainty, Kahneman and Tversky (1979) proposed prospect theory, whereby prospects are coded in terms of gains and losses with respect to a reference point rather than in terms of final wealth. They found for gambling behavior that people's decisions tend to be more sensitive to losses than to gains. Generally, utility and prospect are two completely different concepts. Moreover, although it is not readily evident that prospect theory is necessarily sound for daily travel decisions (Timmermans 2010), the curvature of the model may be useful in some travel contexts.

In traditional utility theory, utility is often defined in terms of final wealth. In prospect theory, change of reference can result in the reverse of preferences. Therefore, it is important to define reference point(s) in a more rational and convincing way. Unlike the concept of traditional utility, relative utility argues that utility is only meaningful relative to some reference point(s), and conceptually it allows the existence of multiple reference points in a systematic way. Prospect theory argues that people's decisions tend to be more sensitive to losses than to gains, where gains and losses are defined with respect to a reference point, but it has not been concerned about specifying reference point(s). To overcome the above shortcomings of the relative utility model and prospect theory, Zhang et al. (2013) integrates them to incorporate simultaneously various context dependences as well as asymmetric and nonlinear responses.

2.5.3.4 Group Decision-Making Mechanisms

In transportation research, individuals have traditionally been regarded as decision-making units or as representatives and independent agents. However, it is well known that individual choice behavior is often influenced by the existence, opinions, and/or behavior of other people, and in some cases, choices are made jointly by a group of people (Thorndike 1938; Corfman and Gupta 1993). Many group-based models have been developed in other disciplines, such as social psychology, marketing research and economics, to describe various aspects (e.g., decision processes and outcomes) of group decisions (Corfman and Gupta 1993). However, although joint activity participation, household resource allocation (e.g., car ownership and use), and task and time allocation are all likely to involve group decisions, research on group decision-making mechanisms is still very limited in transportation (Zhang et al. 2009). Studies of modeling such group decisions in transportation based on group decision-making theories have been conducted since the 1990s (e.g., Timmermans et al. 1992). Currently, increasing numbers of researchers have shown interest in group decision-making mechanisms in various contexts of activity–travel behavior and have confirmed the effectiveness of incorporating group decision-making mechanisms in comparison with traditional models (e.g., Zhang et al. 2002; Vovsha et al. 2003;

Hensher 2004; Bhat and Pendyala 2005; Gliebe and Koppelman 2005; Zhang and Fujiwara 2006b; 2009). In particular, Zhang et al. (2009) have developed a household discrete choice behavior model incorporating heterogeneous group decision-making mechanisms in the context of car ownership behavior. Further efforts should be made to reveal more general group decision rules and to suggest effective survey methods to capture group decision-making processes.

2.6 Methodological Challenges

2.6.1 A Systematic Framework for Urban Environmental Management

To realize a sustainable urban and transportation society, policy makers and other stakeholders are required to make various efforts based on better governance. Such governance should be supported by systematic and scientific approaches, which can generate informative indicators for policy evaluation, decision making, implementation, monitoring, and so on. Segnestam (2002) summarizes the most important lessons learned from the existing studies and suggests that the following aspects are important when developing a set of indicators: (1) development and harmonization of a framework to organize information; (2) definition of selection criteria, indicator sets, and analytical methods/tools; (3) establishment of a participatory/consultative network; (4) data search and development of databases for indicator sets and analytical tools; (5) development of capacities and tools to visualize information and analyze cause–effect relationships; (6) development of test studies for the validation of project results; (7) dissemination of information and tools; and (8) design of actions and implementation. In line with such considerations, a promising indicator framework is the drivers–pressure–state–impacts–response (DPSIR) framework proposed by the OECD (OECD 1999; VRDC 2001). In this framework, social and economic developments exert pressure (P) on the environment, and as a consequence, the state (S) of the environment changes, as in the provision of adequate conditions for health, resource availability, and biodiversity. Finally, this leads to impacts (I) on human health, ecosystems, and materials that may elicit a societal response (R), which directly feeds back to the driving forces (D), or on the state (S), or impacts (I) through adaptation or curative action. The DPSIR framework is useful in describing the relationships between the origins and consequences of environmental problems.

Recognizing the importance of capacity building in environmental management, Zhang and Fujiwara (2007) further introduced the concept of capacity into the DPSIR framework (called the DPSIR+C). Figure 2.4 shows the manner in which the DPSIR+C framework can be applied in the context of urban air quality management. In the figure, the arrows with solid lines indicate how the capacity influences the D–P–S–I–R elements, while the arrows with dotted lines indicate how the

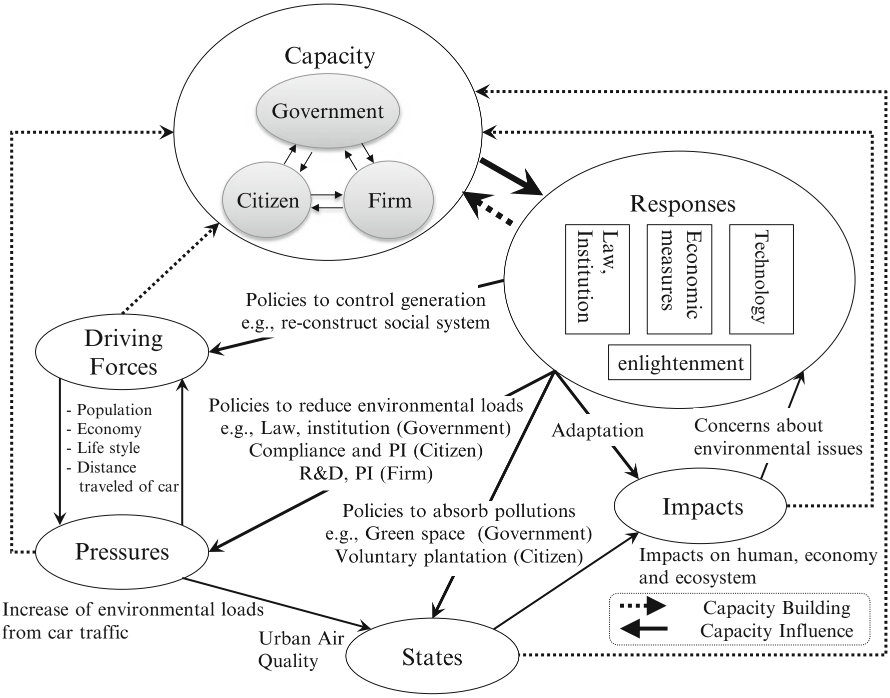

Fig. 2.4 DPSIR+C framework: An example of urban air quality management

capacity should be built, taking into consideration the cause–effect relationships among the D–P–S–I–R elements. It is argued that capacity is the basis of good responses to the D–P–S–I elements. Without such capacity, it is difficult to expect good responses. One can see a two-way relationship between capacity and responses. The arrow from responses to capacity means that lessons/experiences at previous points in time help each actor improve its capacity. The D–P–S–I elements could also contribute to capacity building but in a different manner. For example, in the case of urban air quality management, population and economic growth, lifestyle, and distance traveled may be major driving forces that exert pressure on the environment through the increase of environmental loads from car traffic. Such pressures could inversely influence the driving forces in a positive or negative way. Negative influence refers to the situation whereby an uncontrolled or poorly controlled increase in environmental loads could induce people to travel for longer periods, while positive influence indicates that, for example, a proportion of the population might voluntarily reduce distances traveled in response to an increase in environmental loads. States can be represented by the urban air quality term, which results from the influence of pressure. Impact has been defined in various ways. However, we argue that the extreme impacts of environmental issues are on people (e.g., health and QOL) and natural systems (or ecosystems, e.g., biodiversity). Impacts on human society and natural systems may give rise to concerns over environmental issues. Such concerns lead to a response, such as policy decisions about the enforcement of laws and institutions, economic measures (e.g., road pricing), support and promotion of technological innovation, and enlightenment. Responses could occur to tackle any of the D–P–S–I elements. In the case of driving forces, reconstructing our social system on the basis of an environmentally friendly lifestyle could effectively control traffic generation. Policies to reduce environmental loads include the enforcement of laws and institutions by government, compliance and public involvement by citizens and firms, and technological development by firms. On the other hand, for example, increasing areas for green spaces and voluntary plantation could contribute to the absorption of air pollution. All responses rely heavily on social capacity.

2.6.2 An Integrated Framework for Urban System Design

Urban systems are complex. Dealing with complex systems needs interdisciplinary knowledge. In the above DPSIR+C framework, socioeconomic development models should first be built to provide information on driving forces (D) of urban and transportation activities, which are represented by land-use models and transportation models. Because land-use and transportation systems are usually interrelated, the two models should be integrated. Land use dictates the locations of activities and their intensity; this affects transportation demand and supply, which in turn affects accessibility. As a result, land-use distribution is affected by accessibility and evolves according to changes in accessibility. Various pollutants are emitted as outputs of land-use and transportation systems, which impose pressure (P) on urban systems. Environmental emission models can serve to capture such emissions. Land-use models and transportation models not only can represent various interactions between land-use and transportation systems but also can accommodate various urban policy variables (responses: R). Emissions from urban and transportation activities will be spread over the whole urban space. To capture such dispersion of emissions, air pollution dispersion models are useful. Using such models, states (S) of air quality can be properly described. Land-use changes and emissions from urban and transportation activities can cause damage (i.e., impacts (I)) to ecosystems. Such impacts can be illustrated using ecosystem models. Ideally, all the above models should be integrated (i.e., form integrated urban models) to provide various inputs for environmental impact assessment models in a consistent and systematic way. Environmental impact assessment models should be developed to generate indicators of air quality, QOL and ecosystems, where social capacity for urban system management should also be reflected. The above modeling components are illustrated in Fig. 2.5.

In making policy decisions on low-carbon cities, enforcement of laws and institutional rules, economic measures (e.g., pricing), technological innovations (e.g., new energy and new technology), and enlightenment (e.g., encouraging voluntary behavioral change) should be in the list of alternative policies together with measures for improving the social capacity of urban system management. Technological

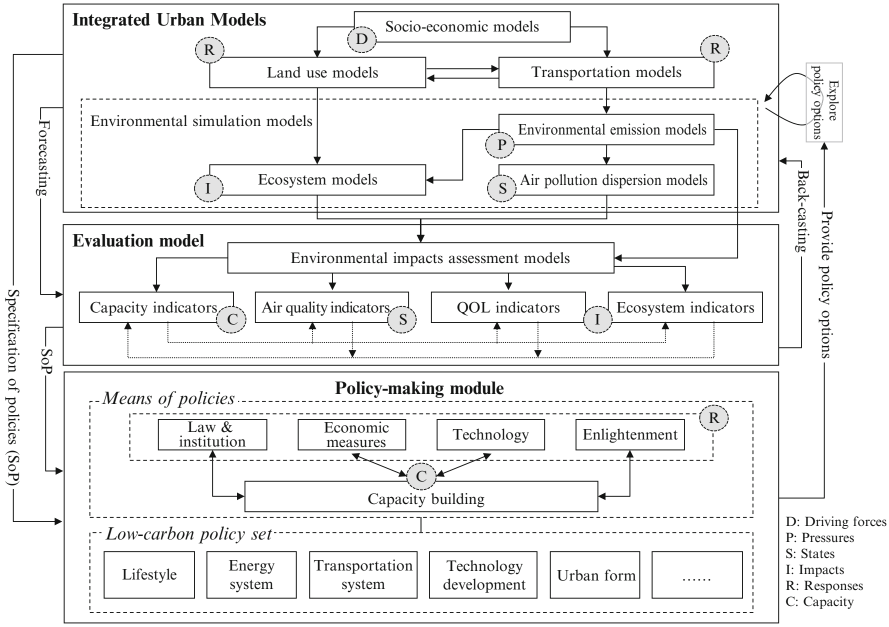

Fig. 2.5 A conceptual integrated framework for urban system design

innovations should take into account the diversity of potential technologies to enhance the survival capability of human society. Rebound effects of new technologies cannot be ignored. Both pull-type and push-type policies should be properly implemented jointly to enhance the effectiveness of policies. At the same time, it should be recognized that there is no one-size-fits-all policy across nations/cities and over time. Local contexts should be reflected. For detailed low-carbon urban policies, urban form, technology development, transportation systems, energy, and lifestyle should be in the choice set.

The key point is to represent changes in both urban systems and the citizens' behaviors, considering people's QOL, environmental capacity and social equity. Both backcasting (top-down) and forecasting (bottom-up) methods will be utilized to derive cost-effective paths that could achieve the desired low-carbon state of an urban system, taking into account the importance of interactive planning and policy making.

2.6.3 Behavioral Studies: From Independent to Integrative Behavior Studies

On average, 60 % of the world's GDP is accounted for by consumer spending on goods and services (UNEP 2009), and 20 % of the world's people—in the US, Europe, Japan and Australia—account for 86 % of the total world expenditure on consumption (UNEP 2002). Households are responsible for approximately 15 % to 20 % of total energy demands in OECD countries (OECD 2001). It is predicted that global energy consumption is set to surge by 44 % between 2006 and 2030, with non-OECD countries seeing a 73 % increase (US-EIA 2009). It is also estimated that five planets would be needed for everyone in the world to adopt the consumption patterns and lifestyles of the average citizen in North America (WWF Living Planet Report 2006). The above facts suggest that encouraging behavioral changes from unsustainable to sustainable lifestyles is important. This is also true in the context of urban and transportation development. In the Eco-Model City Project of Japan (http://ecomodelproject.go.jp/en/doc/D7), 82 cities participated in a contest, in which 80 % of participants claimed that lifestyle change was required to realize low-carbon cities.

To reduce emissions from citizens' urban activities, behavioral changes in various life domains are required, including residences, in-home activities, travel, and out-of-home activities, all of which are supported by various forms of urban infrastructure (e.g., transportation systems, offices, stores, schools, parks, and factories). Various forms of urban infrastructure are managed by governmental sectors. In many countries, the bad effects of the vertically structured administration on citizens' lives have become increasingly remarkable in the field of urban planning and management. To avoid further unease or insecurity about the future lives of citizens, a cross-sectoral approach is required. Civil life, such as work, residence, travel, child care and nursing care, education, shopping, leisure and tourism activities, is usually decided over either long- or short-term periods in various contexts with the consideration of the needs of households and their members and performed at various places under the influence of social networks and time and monetary constraints. To date, several theories have been developed to deal with parts of civil life, such as travel behavior theory, home economics, environmental behavior theory, health behavior theory, human life environment theory, and tourism behavior theory. However, no theory has been proposed to cover the whole life of a citizen in an integrative way. Therefore, it is necessary to establish an innovative theory that can cover major domains of citizens' lives to support cross-sectoral urban planning and management policies (Zhang et al. 2012). For this purpose, further interdisciplinary studies are needed.

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Chapter 3
Comprehensive Travel Demand Analysis in Asian Developing Megacities

Junyi Zhang, Xuesong Feng, and Akimasa Fujiwara

Abstract Transportation issues in developing countries are complicated. To resolve these issues, land-use and transportation systems should be integrated, with an appropriate combination of push and pull measures from a long-term perspective in a comprehensive manner. To support such policy decisions, a four-step travel demand model with a full feedback mechanism is developed, in which trip generation and attraction steps are included in the feedback process by reflecting the influence of transport accessibility. The model is repeatedly estimated based on a much more efficient calculation algorithm. The full feedback mechanism allows us to incorporate the endogenous influence of induced travel demand on various aspects of travel demand. With the help of the above model, various urban and transportation policy scenarios consisting of urban form, public transportation systems, vehicle ownership control, and road networks are examined in the Jabodetabek metropolitan area of Indonesia and Beijing, China, based on a full-scale person–trip survey. Polycentric and transit-oriented urban forms are confirmed to be more environmentally efficient than other policy scenarios.

Keywords Feedback • Four-step travel demand model • Person trip data • Public transportation systems • Urban form

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3.1 Urban Transport Situation of Developing Cities

With the booms in the urban economies of developing countries, the numbers of motor vehicles in their cities have been greatly increasing, especially since the 1990s, because of increased urban populations, better economic conditions, commercial penetration, and probably an increasingly persuasive idea in the developing world of an international lifestyle in which a car is an essential element. In much of the developing world, the annual increase in the number of motor vehicles is more than 10 %, with the number doubling in 7 years (Gakenheimer 1999). Simultaneously, in developing cities, the dramatically increasing travel demands that are in large degree a result of rapid motorization have far exceeded the lagging development of urban transport infrastructure and facilities. The growth rate of urban transport motorization in Jakarta has exceeded 10 % per year, in contrast with increases in road infrastructure expenditure, which has not even reached an annual figure of 1 % (Soehodho 2007). For many reasons, including the imbalance between travel demand and supply, experiences of urban transport situations in developing cities have gone from bad to worse.

First, undeveloped urban transport systems, continuously increasing travel demand and increasingly serious traffic congestion in developing cities have generally increased urban travel time, with the number of destinations accessible within a limited time decreasing. In central Bangkok, traffic speeds have decreased by 2 % per year since the 1980s, and in Rio de Janeiro and Bogota, the average time of a journey to work increased to approximately 107 min and 90 min respectively in the 1990s (Gakenheimer 1999). Such mobility decreases because of serious traffic congestion are even more serious for bus users in developing cities. The average bus travel speed in Beijing decreased from 16.7 km/h in 1990 to 9.2 km/h in 1996, which increased the average travel time of passengers by 22 min (Mao et al. 2002). In 2000, the average bus travel time for one trip in Beijing decreased to approximately 58 min (BMCC and BTRC 2004). This was first because bus routes characteristically follow the highest-volume arteries, which are most afflicted with congestion. Moreover, it is an unfortunate fact that a policy emphasizing expanded road networks rather than improving the bus transit system often worsens this quandary. Decreased mobility has severely harmed the economic growth of these developing cities. For example, the annual economic loss caused by urban traffic congestion in the Jabodetabek metropolitan area of Indonesia, which is the most important economic and strategic metropolitan region, could reach US$0.33 billion for vehicle operating costs and US$0.28 billion for travel delays in 2002 (JICA and BAPPENAS 2004).

Furthermore, the bus systems in developing cities are almost ubiquitously overloaded, and the incomplete urban railway systems in these cities have not played the main role of urban passenger carriers. In Beijing, buses carried approximately 73.54 % of the total public passenger transit volume in 2000; by comparison, the metro carried only 11.51 %, and taxis carried some 14.94 % (BUPA 2002). This overcrowded bus network not only is more susceptible to increasing traffic jams than cars but also contributes greatly to serious traffic congestion. In addition, the inefficient urban railway system overburdens the road traffic network further. It is possible to relieve this congestion by managing buses' right of way, which generally refers to independent lanes or signaling that favors buses, but few cities have been successful simply by applying this, because urban transport in developing countries entails many aspects.

Moreover, the land-use characteristics of developing cities are incompatible with urban transport motorization. For instance, residential densities in the cities of China are as high as 200 to 250 people per gross hectare; however, in European cities, this figure is about 50 people per gross hectare. Streets in Chinese cities usually comprise approximately 10 % of the city area, rather than 25 % as in Western cities, and land use is likely to be more mixed and centralized than in Western cities (Gakenheimer 1999). These figures reveal not only the reasons for the serious traffic situation in developing cities but also the truth that changes in the transport system of a developing city, such as construction of a new highway, have a much greater impact on the travel behavior of citizens than the same changes in a developed city; conversely, the changed travel flows will accelerate the development in the urban structure of the developing city.

Furthermore, to some extent because of the mixed and centralized land-use characteristics explained above, various urban functions are generally distributed haphazardly in the central areas of developing cities. Worse for the cities of developing countries, there are very limited agreements on urban and transport planning approaches, whereas Western countries have cadres of engineers and planners with reasonably consistent perspectives on managing urban and transport problems. These cities tend to borrow methods and professional perspectives from elsewhere and to have professional communities that exchange ideas. This unstable consultation process means that a lack of consistent commitments often results in turbulence in the course of solving urban and transport problems, stalemates when parties attempt to marshal their strength for a particular solution, and rapid changes of strategies over time that prevents any strategy from succeeding. These unreasonable urban function distributions and ineffective urban and transport planning approaches are important reasons for serious traffic congestion, especially during peak traffic hours in developing cities. For instance, one can observe serious traffic concentration every day in DKI Jakarta, the central part of the Jabodetabek metropolitan area because urban functions are concentrated there (JICA and BAPPENAS 2004). This irrationally overcentralized distribution of urban functions and inefficient urban planning can very easily lead to preposterously unbalanced use of the whole traffic network; that is, some roads in the network are very crowded, while others are nearly useless, which exacerbates the lag in the supply of roads in developing cities and further deteriorates the already severe congestion. This disequilibrium in the use of traffic networks because of the prevalent and unreasonable urban structure of developing cities with only a single and overloaded central area can typically appear in the phenomenon of “Tide Traffic” in Beijing, usually occurring in rush hours because of centrally concentrated urban functions within its third ring road (BMCC and BTRC 2004).

Besides the above-mentioned factors, the reasons for the unsatisfactory urban transport situation in the cities of developing countries also include citizens’ intense desire to own cars and their use in developing cities. According to government surveys, Chinese families are prepared to spend 2 years of income for a car that is expected to last for 10 years. In contrast, Americans spend about 27 weeks of their salaries for a car (Gakenheimer 1999). In addition to a lack of adequate road maintenance because of financial difficulties, policy limitations and poor driver discipline, although equally strong or stronger in many East Asian countries than in the West, also cannot be neglected as a cause of serious traffic congestion and accidents in developing cities. In Jabodetabek in 2002, some 9 % of traffic accidents occurred because of potholes and damage to roads, and approximately 73 % of traffic accidents on ordinary roads were caused by careless driving mistakes and violations of traffic rules (JICA and BAPPENAS 2004). Finally, the variety of vehicle types on the streets in developing cities creates difficult problems for efficiency and safety. Many developing cities have passenger vehicles ranging from human traction to high-speed sports cars, and various scales of freight vehicles. Such mixed urban traffic flows made up of various types of motor vehicles and nonmotorized vehicles have made studies of urban transport and management for the cities in developing countries much more difficult than for those in developed countries.

3.2 Study of Urban Transport in Developing Cities

Confronted with the poor state of urban mobility in developing cities because of their rapid development, researchers and planners in the field of transport planning and management have continually sought effective methodologies for analyzing and solving urgent transport issues in these cities. Advanced transport modeling approaches such as some of the disaggregate activity-based modeling methods (e.g., McNally 2000a), which have been efficiently applied to the study and improvement of urban transport conditions in cities in developed countries, have been used in attempts to analyze and resolve the problematic urban transport problems in developing cities. However, valid analyses of the urban transport studies of developing cities are very difficult, because elementary trip survey data are still quite scarce, and the available data mostly are of very poor quality and often are not shared among planning agencies (Boyce and Xiong 2007). Thus, advanced modeling techniques, which usually require more detailed trip and/or activity data, are very difficult to apply. Therefore, the conventional aggregate four-step modeling process, which is customarily estimated sequentially, is still the most widely applied method because of its practicability (McNally 2000b; Siegel et al. 2006).

The conventional four-step model includes the usually top-down estimated four steps of trip generation and attraction, trip distribution, travel modal split and

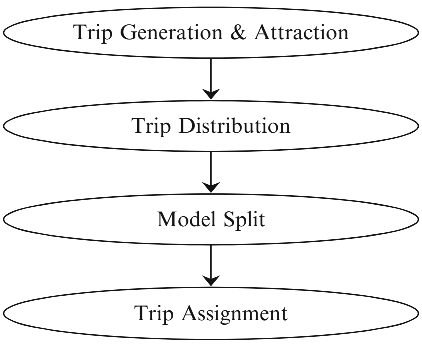

Fig. 3.1 Conventional four-step modeling approach

trip assignment, as shown in Fig. 3.1. The modeling process might be best viewed in two stages (McNally 2000b): (1) various characteristics of travelers and the land-use–activity system (and to a varying degree, the transport system) are "evaluated, calibrated, and validated" to produce a nonequilibrated measure of travel demand (or trip tables); (2) this demand is loaded onto the transport network in a process that amounts to formal equilibration of route choice only, not of other choice dimensions such as destination, mode, time of day, or whether a person travels at all. The initial development of models of trip generation, distribution, and diversion in the early 1950s led to the first comprehensive application of the four-step model system in the Chicago Area Transportation Study (Weiner 1997). The US federal legislation requiring "continuous, comprehensive, and cooperative" urban transport planning in the 1960s fully institutionalized the four-step model. In this four-step modeling framework, in theory derived from demand for activity participation, travel is modeled in practice with trip-based rather than activity-based methods. As the conventional forecasting sequence proceeds, the influence of activity characteristics decreases, and that of trip characteristics increases.

Because of the lack of a behavioral decision foundation, although it has been moderately successful at the aggregate level, the conventional four-step modeling approach has failed to perform in most relevant policy tests, on either the demand or the supply side. The application effect of the conventional four-step model adopted in the urban transport study of developing cities has always appeared unclear and unpersuasive when confronted with the more complicated urban transport situations in the cities of developing countries, as explained above. As a result, development is urgently required of new urban transport modeling techniques suitable for urban transport planning studies of developing cities facing many problems, such as trip survey data scarcity, financial difficulties and serious urban transport conditions.

3.3 Interdependencies in Urban Transport Planning Systems

To establish and apply an efficient means of studying urban transport in developing cities, the comprehensive urban transport planning system should be first analyzed and understood from an integrated viewpoint. In the urban transport planning structure introduced by Manheim (1979) and expanded by Florian et al. (1988), as shown in Fig. 3.2, travel demand (**D**) is determined by spatial distribution of land use and

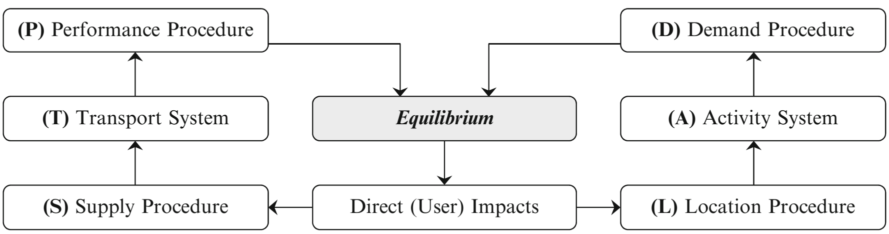

Fig. 3.2 Interdependent feedback mechanism in urban transport planning system

demographic and/or economic activities (**A**) that occur on that land, which are decided by an activity location choice procedure (**L**) influenced by transport actions impacted by dynamic travel flows in transport networks. Moreover, the actuality of the transport system (**T**) is, of course, the main factor in its performance (**P**) and is gradually formed by transport supply procedure (**S**), which can be regarded as a reflection of transport actions impacted by dynamic transport flows. Conversely, according to the equilibrium between travel demand (**D**) and performance (**P**) of the transport system, travel flows should directly impact the trip behavior of travelers. These successive impacts should be on the activity location choice procedure (**L**), transport supply procedure (**S**), activities on land used for particular purposes (**A**), the transport system (**T**),and finally on travel demand (**D**) and performance of the transport system (**P**). Consequently, a new equilibrium will be reached. Because of this interdependent feedback mechanism, various components of the urban transport planning system are integrated in a dynamic and general manner. Because of the urban transport development characteristics of developing cities, especially the fast and very distinct mutual effect between urban transport evolution and land-use changes, the behavior-based interactive feedback among various factors of the urban transport planning system discussed above could be much more evident. As a result, much greater importance should be attached to urban transport studies in developing cities.

3.4 The Reality of Urban Transport Planning in Developing Cities

Besides analyzing the urban transport planning system, it is necessary to understand the reality of urban transport planning in developing cities to improve studies of urban transport planning in cities in developing countries. Typically, it is discovered that urban transport infrastructure improvement is the primary factor in the development of a city. In other words, land used for construction of urban transport infrastructure facilitates urban transport activities and as a result boosts the prosperity of the urban economy. Furthermore, a prosperous urban economy will stimulate other urban activities, such as recreation activities, which will develop the land used for these activities and deservedly improve travel demand and in turn require more urban transport infrastructure. This interactive circle has become the driving force for urban growth of cities in developing countries, which could be utilized by their governments to build a more efficient urban transport system, or conversely could create a vicious cycle in which road construction can never catch up with the increasing demand for travel, and with more roads, much more serious traffic jams would occur. According to a study of the Ayala Planned Area of Makati in the Philippines, transport infrastructure in this area was developed not only to increase accessibility to/from and within the area but also to guide and support the other designated urban land uses (Kishiue et al. 2005). In contrast, in Beijing, because insufficient attention was paid to integrated urban land-use and transport planning, the urban traffic situation has worsened with the completion of the fifth ring road.

For the developing cities that currently face urgent and complex urban transport problems because of a lagging transport infrastructure supply and continually increasing travel demand resulting from rapid development, it is essential to decide exactly whether a large-scale transport infrastructure construction project would yield the maximum benefit and avoid the above vicious cycle owing to lack of comprehensive design. Therefore, the most important issue for urban transport research on cities in developing countries is to consider the interactive relationship among different ingredients of the urban transport planning system; that is, the interdependent feedback mechanism discussed above, especially the evident interaction between land use and transport. The simple application of the traditional four-step model without feedback would certainly be insufficient to analyze quite complicated urban transport issues, much less to resolve them.

3.5 Feedback Modeling Study for Developing Cities

As can be seen from the above discussion, it is necessary to import the behavior-based feedback interdependence among factors of the urban transport planning system into the study and decision-making process, especially for developing cities confronted with serious and complicated urban transport development problems. To achieve this, advanced disaggregate modeling studies using data directly collected from individual travelers have been developed and improved since the late 1970s. However, as explained above, these new methods require more detailed trip and/or activity data that are very difficult to collect in developing cities. The collection of such data suffers from poor data quality, and budget and human resource constraints related to survey implementation. Because even poor-quality survey data are extremely limited and not adequately shared, it is quite difficult to apply these advanced approaches to urban transport studies of developing cities and to obtain valid analysis results. Moreover, many other integrated models have previously been developed to consider the interactive relationships between urban transport and land use comprehensively, but these integrated models also require a good deal of detailed input data. On the other hand, although popular in practice, the trip-based and usually top-down estimated conventional four-step modeling procedure, generally estimated sequentially with serious propagated uncertainties (Zhao and Kockelman 2002), has unreasonably disregarded the feedback mechanism shown in Fig. 3.2. Therefore, it generally does not perform satisfactorily in urban transport studies of developing cities.

In view of the severe data limitation and the urgent need for integrated consideration of the interrelationship among essential aspects of urban transport planning systems in the analysis of decision making in developing cities, the feedback mechanism discussed above is feasible, reasonable and necessary. The effectiveness of the travel demand model with feedback has been confirmed since the 1950s in the context of developed countries (Levinson and Kumar 1993; Boyce and Xiong 2007; Boyce 2002). Boyce et al. (2008) further conducted a sensitivity analysis of different convergence methods to estimate the feedback model and emphasized the contemporary importance of improving feedback models. On account of the rapid growth of developing cities today, frequently influenced by urban transport development and rapidly changing land use in these cities, people's travel behavior swiftly changes within a quite short time. Thus, travel behavior can have a reverse effect on urban transport improvements and the transformation of land use. From an alternative macro perspective, trip generation and attraction volumes in urban areas, trip origin and destination choice, and shares of various travel modes are easily affected by the immediate performance of the improved transport networks. Because of these characteristics of urban transport in developing cities, the feedback computation is first iteratively imported into all four steps of the conventional modeling process in this study. The study now establishes a new aggregate four-step travel demand prediction model with a feedback process.

In this research, the iterative importation of the feedback into each of the four steps of the modeling analysis is a different process from formulating the model components at all these steps as an optimization problem solved directly using convex combination methods, as proposed, for example, by Safwat and Magnanti (1988). The feedback model proposed here is also different from previous iterative feedback models such as those by Levinson and Kumar (1993), Boyce et al. (1994), Walker and Peng (1995) and Boyce and Xiong (2007), which always exclude the step of trip generation and attraction from the feedback procedure. In this study, a trip generation and attraction analysis is introduced into the feedback procedure by applying the indicator of transport accessibility for each trip analysis zone to give more comprehensive consideration to the urban transport characteristics of cities in developing countries. As to the feedback procedure convergence of the proposed model, the Direct Feedback (DF) solution presents a more efficient result than the alternatives. This is in contrast to the dominant opinion that DF is the worst, or at least not the best, approach to feedback procedures (e.g., Boyce et al. 1994; Walker and Peng 1995; Lan et al. 2003; Boyce et al. 2008).

Furthermore, improvement of transport networks usually leads to improved transport accessibility and consequent spatial distribution changes in such factors as population and car ownership, which are used to explain trip generation and attraction in the proposed feedback model. Such influences may be even more remarkable in developing cities. Nevertheless, the proposed feedback model deals exogenously with these explanatory variables in the step of trip generation and attraction and cannot logically represent distribution changes resulting from changes in transport networks' performance. As a result, the proposed feedback model is further improved to create an integrated travel demand forecast model by adding an Aggregate Multinomial Logit (A-MNL) model to describe endogenously the distributions of the variables used to interpret trip generation and attraction, which are easily influenced by the performance of transport networks.

Because the urban transport issues discussed above are typical of both the Jabodetabek metropolitan area and Beijing, and quite high-quality Person Trip (PT) survey data for these two areas can be obtained, these were selected as the target study areas for this research. PT data for Jabodetabek in 2002 and Beijing in 2000 were provided by the Japan International Cooperation Agency (JICA). The analyses of the validities of the proposed feedback and integrated model estimations and applications were mainly performed with the *TransCAD* software.

3.6 An Improved Four-Step Travel Demand Model with Feedback

Considering that all the conventional four steps of the modeling framework are interrelated in a behavior-based mechanism, it is necessary to incorporate the feedback procedure into each step to reflect properly the behavioral interdependence among the various components of urban transport planning systems, especially for urban transport studies of developing cities. Accordingly, establishment of a new travel demand model has been attempted, with each prediction step linked in two-way manner through an iterative feedback practice. This is quite different from the traditional four-step model allowing only for a one-way sequential process. The general configuration of this new aggregate feedback model is presented in Fig. 3.3. The model is briefly explained below; for details, refer to Feng et al. (2007).

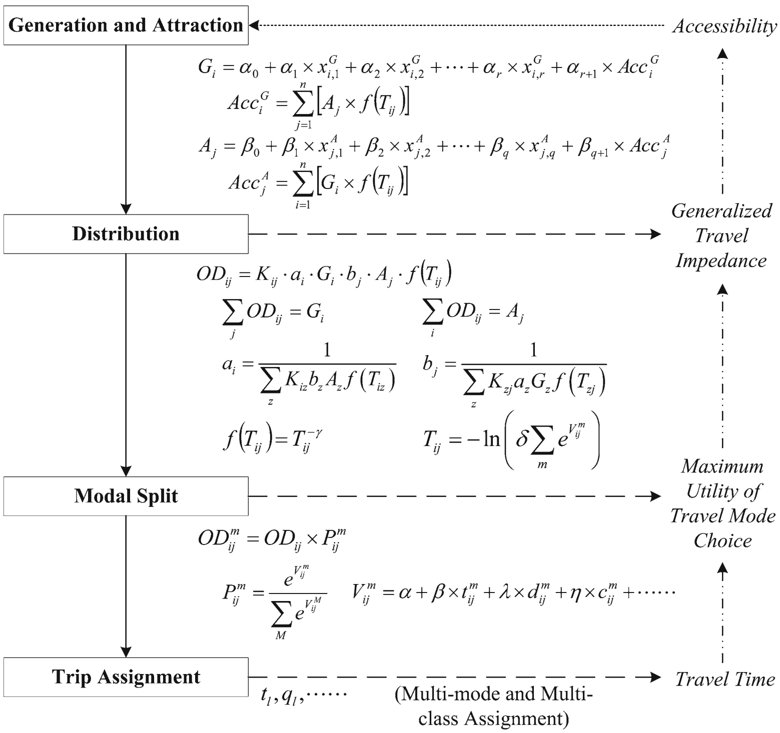

Fig. 3.3 The proposed feedback travel demand model

The first step of the feedback process in the proposed model shown in Fig. 3.3 is modal split, represented using the Multinomial Logit (MNL) model. The inclusive values of various travel modes (i.e., *maximum utility of travel mode choice*) are used to represent the overall performance of transport networks. Subsequently, an inverse power function of these inclusive values is introduced into the Doubly Constrained Gravity (DCG) model adopted in the trip distribution step to generate the *generalized travel impedance* between each OD (origin–destination). Next, this generalized travel impedance is used to calculate the transport *accessibility* of each Trip Analysis Zone (TAZ). Thereafter, *accessibility* is incorporated into the trip generation and attraction step as an explanatory variable of the Multiple Linear Regression (MLR) models applied to the study of trip generation and attraction at each TAZ. With the estimation of the MNL, DCG and MLR models successively completed, the process obtains new estimates of trip generation and attraction, trip distribution, modal split shares, and finally trip assignment results. For the trip assignment study, with a view to mixed traffic flows typically consisting of various kinds of motor vehicles and labor vehicles in developing cities, a link-based Multimode and Multiclass Assignment (MMA) method (Caliper Corporation 2004) is applied. This considers not only the interaction between bus and road networks with the bus preassignment results preloaded onto road networks but also the interactive effect among different types of vehicles. Passenger car equivalence for all vehicles was established using the Highway Capacity Manual (NRC 1985). Based on the results of trip assignment using this MMA method, *maximum utility of travel mode choice* is changed according to the new *travel time* on each link of the road network. Now, the next iteration of this feedback estimation process can begin. This iterative process continues until certain convergence criteria are achieved.

In contrast, the conventional four-step model is usually estimated in a top-down manner from the trip generation and attraction step by estimating the MLR models according to variables such as present population and availability of jobs in each TAZ. Based on the results of predicted trip generation and attraction in each TAZ and the DCG model calibrated according to present trip distribution, it is possible to derive a new estimate of the OD matrix that is imported into the MNL model to obtain OD matrices for various travel modes. Finally, these OD matrices are assigned to transport networks. It is obvious that such a one-way sequential estimation procedure without feedback cannot represent the behavior-based interdependence mechanism explained above, which is especially important for studies of modern urban transport in developing cities. Moreover, it is also found that in addition to the same data input into the top-down estimation procedure of the conventional four-step model, no additional data are required for the iterative estimation process of the newly developed feedback model, which is very important for such studies in view of the serious lack of research data for most developing cities.

Furthermore, all four steps from trip generation and attraction to trip assignment in the proposed feedback model in this study are incorporated and estimated using the iterative technique explained above. This is different from formulating the model components from each of the four steps in the modeling approach as an optimization problem solved directly based on convex combination methods, as proposed by Safwat and Magnanti (1988), for example. For the comprehensive urban transport studies of the cities in developing countries confronted with serious restrictions to research data, as explained above, it is difficult to find efficient, feasible and practical solutions to such optimization problems in the management of urban transport.

In addition, the feedback process of the newly developed feedback model described above differs quite significantly from most estimation procedures in the conventional iterative feedback models previously proposed by, for example, Levinson and Kumar (1993), Boyce et al. (1994), Winslow et al. (1995), Miller (1997), Boyce (2002), Bar-Gera and Boyce (2006) and Boyce and Xiong (2007). Their estimation procedures are initiated from the trip distribution step according to an initially assumed travel impedance matrix and the initial input of trip generation and attraction. Then the estimation process proceeds in a backward manner (step by step) until trip assignment. Depending upon whether a link-based or a route-based assignment algorithm is adopted, either the impedances of the shortest routes or the average impedances of routes used (usually travel time and travel cost) are only returned to the travel impedance matrix in the trip distribution step. Without the incorporation of the trip generation and attraction analysis into the feedback process, the iterative procedure continues between the steps of trip distribution and trip assignment until convergence is achieved. Simply considering the influence of the changes of travel impedances between TAZs on trip distribution, the feedback processes in previous feedback models have neglected the notable effect on the trip matrix of the continually changing trip generation and attraction volumes, especially in the TAZs of developing cities with soaring travel demand because of their prosperous urban economies and rapid urban growths.

The feedback model described above was estimated and its effectiveness confirmed empirically based on data collected from the Jabodetabek metropolitan area in 2002 and Beijing in 2000 (Feng et al. 2007). With these estimation results, it is now possible to construct simulation analyses of various integrative scenarios for the comprehensive urban and transport developments of these two megacities in the future. With the distinct scenarios having contrasting effects, this study explores some sustainable urban and transport policies from the perspectives of protection against traffic emissions and relief from serious traffic congestion. Some scenarios are assumed based on information from published governmental sources, and others are best practice policies. To evaluate the effects of policies, those scenarios without any policy implemented (BAU: Business As Usual) are taken as a reference.

3.7 Analysis of Urban Transport Development in Jabodetabek Metropolitan Area

3.7.1 Scenarios for Urban Transport Development to 2020

Regarding the future comprehensive urban transport development of Jabodetabek, a total of eight simulation scenarios are assumed for 2010 and 2020, which are two targeted planning years for this metropolitan area (JICA and BAPPENAS 2004).

Table 3.1 Scenarios for the urban transport development in Jabodetabek till 2020

Scenarios	Road network	Urban form	Motorcycle ownership	Public transport systems
S1	Undeveloped	Uncontrolled	Uncontrolled	Unimproved
S2	Developed	Uncontrolled	Uncontrolled	Unimproved
S3	Developed	Uncontrolled	Uncontrolled	Improved
S4	Developed	Uncontrolled	Controlled	Unimproved
S5	Developed	Compact City Development (CCD)	Controlled	Unimproved
S6	Developed	Transit-Oriented Development (TOD)	Controlled	Unimproved
S7	Developed	Poly-Center Development (PCD)	Controlled	Unimproved
S8	Developed	Poly-Center Development (PCD)	Controlled	Improved

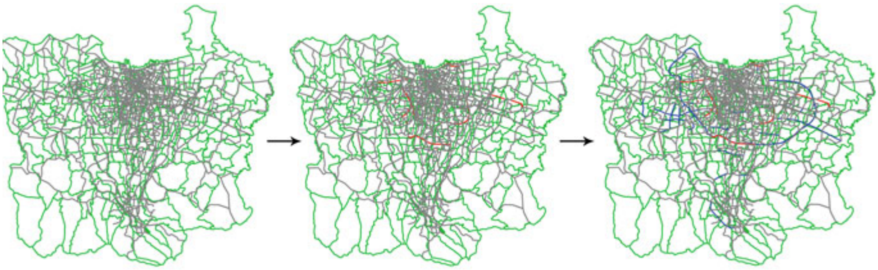

Fig. 3.4 Development of the road network in Jabodetabek in 2010 and 2020

These scenarios are summarized in Table 3.1. First, the “Undeveloped” *Road Network* shown in this table indicates that the road networks in Jabodetabek in 2010 and 2020 will remain the same as in 2002. Conversely, the “Developed” case assumes that the road network in Jabodetabek will be developed according to the governments’ plans for 2010 and 2020, which are shown in Fig. 3.4. In this figure, the red and blue lines represent new roads (some ring roads and connector roads to the city center) to be constructed successively until 2010 and 2020 respectively.

The “Uncontrolled” *Urban Form* refers to the case in which daytime population, households and employment in each of the 336 TAZs will grow at an average annual rate of 5 %. As a result, the total number of households in Jabodetabek is assumed to increase from 5,857,931 in 2002 to 8,016,983 in 2010 and 11,867,093 in 2020, the secondary employed population from 1,342,982 in 2002 to 2,116,203 in 2010 and 3,241,933 in 2020, and the daytime population from 19,969,575 in 2002 to 23,397,540 in 2010 and 28,521,471 in 2020, respectively. In comparison, Compact City Development (CCD) refers to the population growth in central urban areas, Transit-oriented Development (TOD) assumes that growth of future population will be observed only along the bus and railway lines, and Polycenter Development (PCD) means that future growth of the population will be concentrated in the four subcenters in suburban areas. Specifically, the above-mentioned total net increase of population (e.g., 3,427,965 = 23,397,540 in 2010—19,969,575 in 2002 for the

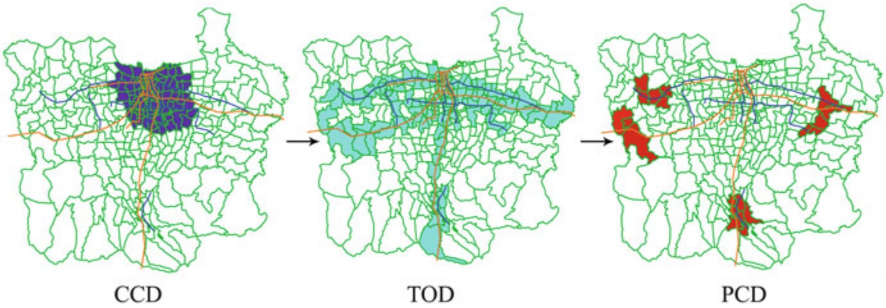

Fig. 3.5 Controlled urban forms for the development of Jabodetabek till 2020

daytime population) will be distributed evenly in the zones in central urban areas under CCD, in the zones along the bus and railway lines under TOD, and in the four subcentral areas under PCD. These controlled urban forms are shown in Fig. 3.5.

Moreover, the annual rate of increase in the number of motorcycles in each TAZ is selected as an important policy factor in the comprehensive urban transport development scenarios presented in Table 3.1. With respect to *Motorcycle Ownership* shown in Table 3.1, the "Uncontrolled" scenarios indicate that the growth ratio of motorcycles in each TAZ is set at 5 % annually from 2002 to 2020, and the "Controlled" ones indicate that the growth ratio is assumed to decrease by 1 % annually.

Finally, the "Improved" scenarios for *Public Transport Systems* in the future assume that 50 % of the people taking car and motorcycle trips in 2002 will change to bus and railway services in the future. Such a modal shift could be realized by improving service levels, such as in terms of travel time, cost, frequency, sanitation, safety, and service manner.

3.7.2 Distinct Performances of Different Scenarios

Although many indicators of degree of congestion (e.g., travel speed and volume:capacity ratio of each link on the traffic network) and average daily traffic emissions (of CO, NO_x, SO_x, HC and PM) have been calculated to compare the assumed outcomes of the eight simulation scenarios shown in Table 3.1, because the change in their values shows similar patterns and trends, only the forecast results of travel speeds on each link of the road network and the total amounts of traffic emission of CO (one of the main representative traffic emission pollutants in Jabodetabek) are compared in Figs. 3.6 and 3.7, respectively, for these eight scenarios. The values of the emission factors adopted here are in accordance with the work of Purwanto (2001).

As shown in Figs. 3.6 and 3.7, *S8* performs best in increasing travel speed and reducing traffic emission from both short (the year 2010) and long (the year 2020) runs. In other words, if possible, the implementation of the full policy package is the best option in the case of Jabodetabek. (As for scenario *S8*, controlling the number

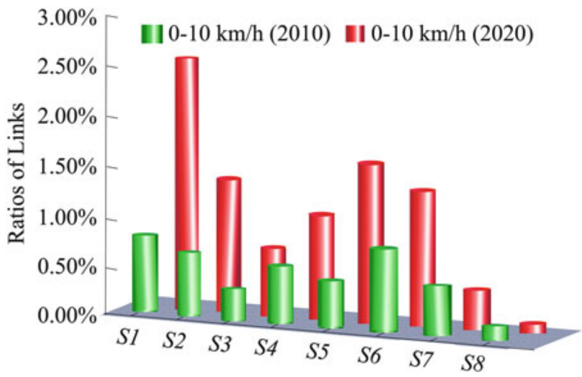

Fig. 3.6 Ratios of road links with speeds lower than 10 km/h in Jabodetabek; Unit: %

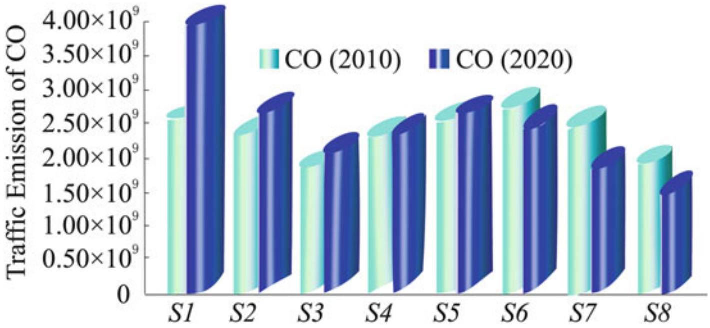

Fig. 3.7 Total volumes of average daily traffic emission of CO in Jabodetabek; Unit: gram

of motorcycles influences trip generation; PCD impacts the main locations of trip generation and attraction, and consequently the whole trip distribution, affecting such aspects as spatial distribution of population and employment. Changing mode shares affects public transport systems, and developing road networks affects trip assignment results. In addition, these actions contribute simultaneously in an integrated manner through the feedback procedure.) Obviously, such a complete policy package is costly. Considering that it may be difficult to realize a 50 % shift from private automobiles to public transport systems, scenario *S7* can be regarded as the second best option, especially from the long-term perspective. Scenario *S3* has very similar effects to *S7*, which suggests that if we could increase the share of using public transport systems, environmentally sustainable transport could also be realized without restricting urban growth or motorcycle ownership within the urban area. To balance the increase in travel speed and the reduction of environmental emissions, scenario *S4* seems promising in the sense that promoting improvement in road networks while controlling motorcycle ownership effectively could also have a satisfactory effect. Comparing scenarios *S5* and *S6*, one can observe that TOD and CCD have similar effects. The stronger effects of PCD suggest that development of subcenters in suburbs could contribute more than CCD or TOD.

Table 3.2 Comparison between the feedback model and the conventional model

Scenarios	0–5 km/h (‰)	5–10 km/h (‰)	10–15 km/h (‰)	15–20 km/h (‰)	20–25 km/h (‰)	25–40 km/h (‰)	CO (gram)
Conventional travel demand model without feedback mechanisms							
S1	27.9	54.1	39.6	40.8	38.4	140.7	6.37E+09
S2	24.4	22.3	18.2	21.0	20.8	107.1	5.23E+09
S2-S1	−3.6	−31.9	−21.3	−19.9	−17.6	−33.5	−1.15E+09
Proposed travel demand model with feedback mechanisms							
S1	6.2	19.7	27.4	29.6	25.8	101.1	3.94E+09
S2	5.1	8.4	8.5	9.3	10.7	51.6	2.67E+09
S2-S1	−1.1	−11.4	−18.9	−20.3	−15.1	−49.5	−1.27E+09

To confirm the difference between the application of the newly devolved feedback model and that of the traditional four-step model without incorporating a feedback mechanism, results of simulations of scenarios *S1* and *S2* were compared with those forecasted by the traditional four-step model. The results are compared in Table 3.2. It is obvious that the simulations of *S1* and *S2* by the conventional model without feedback underestimate the changes in total traffic emission volumes of CO, overestimate changes at lower travel speeds (0–15‰) and underestimate the average changes at higher speeds.

3.8 Analysis of Urban Transport Development in Beijing

3.8.1 Scenarios for Urban Transport Development Until 2020

Concerning the future urban transport development in Beijing, seven comprehensive scenarios are assumed and shown in Table 3.3 for the year 2020. The "undeveloped" *Road Network* and "unimproved" *Public Transport Systems* shown in this table indicate that the road network and the bus and subway lines in the year 2020 will remain unchanged from the year 2000. In contrast, the "developed" and "improved" cases for *Road Network* and *Public Transport Systems* are shown in Fig. 3.8, in which the gray lines represent the road network, and the blue and red lines mean the bus and subway lines respectively.

For the *Urban Form* shown in Table 3.3, the TOD represents future population growth, mainly in the TAZs along the bus and railway lines. Because the bus lines are able to serve each of the 340 TAZs in the urban area of Beijing, as clearly shown in Fig. 3.8, TOD is defined according to population, number of students and employment in each TAZ, with average annual rates of increase of 1.33 %, 1.50 % and 0.50 %, respectively. These rates are estimated according to the development statistics of Beijing in recent years. Consequently, it is assumed that the total population of Beijing will increase from 13.82 million in 2000 to 18.00 million in 2020. In contrast, CCD is represented by assuming that future population growth will occur

Table 3.3 Scenarios for the urban transport development in Beijing till 2020

Scenarios	Road network	Urban form	Car ownership	Public transport systems
S1	Undeveloped	TOD	Uncontrolled	Unimproved
S2	Developed	TOD	Uncontrolled	Unimproved
S3	Developed	TOD	Uncontrolled	Improved
S4	Developed	TOD	Controlled	Unimproved
S5	Developed	CCD	Controlled	Unimproved
S6	Developed	PCD	Controlled	Unimproved
S7	Developed	TOD	Controlled	Improved

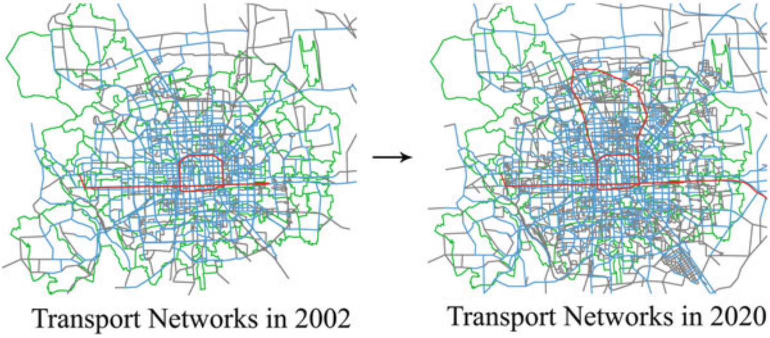

Fig. 3.8 Hypothetical transport networks development in Beijing from 2000 to 2020

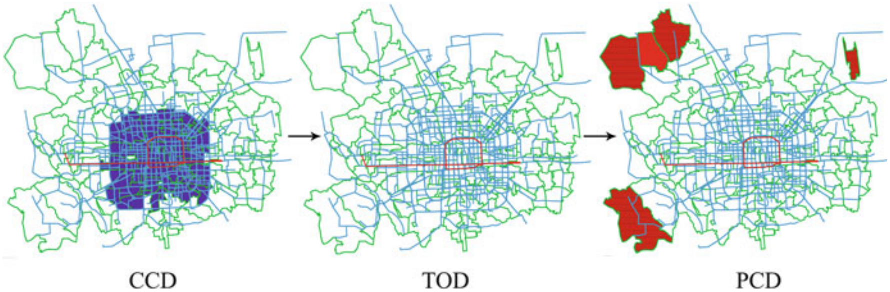

Fig. 3.9 Controlled urban forms for the development of Beijing till 2020

mainly in the TAZs in the central urban area. PCD assumes that population growth will be concentrated mainly in the TAZs of three suburban subcenters. The above-mentioned net average increases in total population are distributed to the TAZs in the central urban area for CCD and the three subcentral areas for PCD, respectively. These controlled urban forms of urban transport development in Beijing are shown in Fig. 3.9.

With respect to *Car Ownership* shown in Table 3.1, the "uncontrolled" scenario indicates that the rate of increase for each TAZ is set at 5.94 % annually from 2000

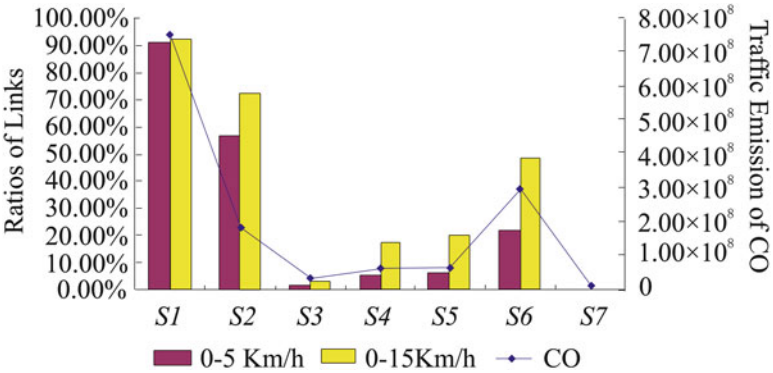

Fig. 3.10 Ratios of road links with low speeds and total volume of CO from traffic emission; Unit of ratios of road links: %, Unit of CO volume: gram

to 2020, a figure based on annual rates of increase in motor-vehicle ownership in Beijing in recent years. Under the "controlled" scenario, the growth ratio is assumed to decrease by 1 % annually.

3.8.2 Distinct Performances of Different Scenarios

To compare the effects of scenarios on urban transport development in Beijing until 2020, changes of travel speed at each link and the total amount of traffic emissions of CO (also one of the main traffic emission pollutants in Beijing) are taken as two indicators. The values of emission factors adopted here are calculated based on studies by He and Wang (2006) and Wang et al. (2005). The predictions of the scenarios presented in Table 3.3 are compared in Fig. 3.10.

According to the study results shown in Fig. 3.10, scenario *S7* is most effective in relieving traffic congestion and protecting the environment. That is, the full implementation of such a policy package is the best option in the sustainable urban transport development of Beijing to 2020. Because the full policy package could be costly and scenario *S3* has similar effects, the improvement of public transport systems could result in an environmentally sustainable transport society, even without control of urban growth and car ownership within the urban area of Beijing. Moreover, by balancing the increase in travel speed and the reduction of emissions, scenario *S4* also seems promising in the sense that promoting the improvement of road networks and effective control of car ownership could provide a satisfactory solution. In addition, comparing the scenarios *S4* and *S5*, it can be observed that TOD and CCD have similar effects. Finally, considering the quite poor PCD effects caused by the huge traffic flows between the subcenters and the main central area, it can be concluded that TOD is more suitable as a future urban development form for Beijing.

3.9 Different Sustainable Urban Forms of Jabodetabek Metropolitan Area and Beijing

According to this study of the application of a proposed feedback model for sustainable urban transport development in Jabodetabek and Beijing, it is first found that without effective action, overall urban transport conditions in both these megacities will deteriorate in terms of not only aggravated traffic congestion but also exacerbated air pollution. Therefore, comprehensive implementation of various policies including construction of new roads, decisions on suitable urban form, restriction of increases in motor-vehicle ownership and improvement in public transport systems is the best way to prevent the current severe urban transport situations in these two developing cities from becoming much worse and to develop their urban transport systems in a sustainable manner. Considering that an integrated policy package would be costly and therefore quite difficult to implement fully in view of the parlous financial state of most developing cities, efficient improvement of public transport systems is an economic and effective means of achieving sustainable urban transport development in developing cities.

At the same time, it is also apparent that polycenter development is better than the alternative urban forms for urban transport in Jabodetabek. This will supposedly result mainly from changes in the distribution of land-use factors. In comparison, the application of the polycenter urban form in Beijing according to the proposed feedback model cannot effectively guide the reasonable distribution of land use, especially that of employment, and consequently it has a quite poor effect because of the huge traffic flows between subcenters and the main central area. The simulation results thus suggest that a transit-oriented urban form is more suitable. The appropriate forms of sustainable urban transport development in Jabodetabek and Beijing require further study and substantiation in future research.

3.10 Conclusions and Future Perspectives

3.10.1 What We Have Done?

Owing to the prosperity of urban economies in most cities in developing countries, especially since the 1990s, the rapidly increasing travel demands in these cities because of the rapid progress of urban transport motorization have far exceeded the seriously lagging development of urban transport infrastructure and facilities. Mainly because of such imbalances between travel demand and supply, urban transport conditions in most developing cities have gone from bad to worse. Severe traffic congestion and vast amounts of traffic emissions have led to substantive economic losses. As a result, in view of these urban transport planning characteristics, extreme lack of survey data, and urgent need for integrated consideration of behavior-based relationships among various essential elements of the urban transport planning system, it is necessary, reasonable and feasible that studies should incorporate feedback mechanisms into models of urban transport planning and decision-making analyses of developing cities confronted with serious urban transport issues.

In this research, a new four-step travel demand prediction model with feedback has been developed. It differs from the conventional four-step model, which, irrationally, is estimated in a top-down sequential manner but is still widely applied because of its practicability. Moreover, the iterative importation of feedback in this study is also dissimilar to previous feedback modeling studies, which are traceable to the feedback method proposed by Evans in 1973 and 1976 (Lan et al. 2003) and categorized by Lam and Huang (1992) into: (1) formulations of the model components as an optimization problem solved directly based on convex combination methods, and (2) iterative feedback modeling usually excluding the trip generation and attraction step from the feedback procedure. The trip generation and attraction analysis here is introduced into the feedback procedure of the proposed model through an indicator of transport accessibility for each trip analysis zone. This feedback model provides a more practical way to reflect appropriately the behavior-based interdependence between transport networks and various aspects of travel behavior using a four-step modeling framework. This method is reasonable and necessary for urban transport studies of modern developing cities with rapid urban growth. Moreover, a multimode and multiclass assignment method is adopted to consider the interactions between types of trips on different networks. As a result, the goodness-of-fit indices for the model estimation of the proposed feedback model are much more satisfactory than the estimation results of the traditional four-step model.

The forecasts of the proposed feedback model for sustainable urban transport development of Jabodetabek and Beijing show that if no effective action is taken, traffic congestion and air pollution in both these megacities will worsen considerably. Therefore, comprehensive implementation of various policies is the best way to prevent the current severe urban transport conditions in these two developing cities worsening and to develop their urban transport systems in a sustainable manner. Considering that an integrated policy package would be costly and therefore quite difficult to implement fully in view of the parlous financial state of most developing cities, efficient improvement of public transport systems is an economic and effective means of achieving sustainable urban transport development in developing cities. At the same time, it is also apparent that polycenter development performs better than the other urban forms for the sustainable urban transport development of Jabodetabek. This is attributable to changes in the distribution of land-use factors. In comparison, the application of the polycenter urban form in Beijing in the proposed feedback model cannot effectively direct the reasonable distribution of land use, especially the distribution of employment, and consequently has a quite poor effect because of the huge traffic flows between subcenters and the main central area. The simulation results suggest that the transit-oriented urban form is more suitable for the development of sustainable urban transport in Beijing.

3.10.2 Further Improvement

1. Adding a New Step to the Four-Step Feedback Model
   An important issue ignored in the feedback modeling approach is the influence of transport networks on changes in the numerical values of the explanatory variables such as population factors and car ownership, of the trip generation and attraction models. Improvements in transport networks usually lead to improved accessibility, which consequently may result in changes in residential and workplace choice behavior across urban space. Such influences may be remarkable, especially in developing cities. To represent such distribution changes and to reflect behavioral mechanisms in a logical manner, Feng et al. (2009) improved the four-step model with feedback by adding the step of spatial population distribution based on the concept of spatial autocorrelation (Getis et al. 2004), where the spatial population distribution is further reflected in the influence of accessibility. With the same person trip data collected in Beijing in 2000, it is empirically confirmed that the integrated model is more accurate than either the feedback model or the conventional model (i.e., the sequentially estimated traditional four-step model). In particular, it is revealed that ignoring the added spatial population step can result in underestimation of environmental emissions. Using the model estimation results, several comprehensive policy scenarios for the future urban and transport development of Beijing are compared using the feedback and integrated models. It is consistently confirmed by both models that comprehensively improving public transport systems and road networks while restricting car ownership is best for the sustainable development of Beijing in terms of urban traffic congestion relief as well as environmental protection.
2. Backcasting Analysis
   Regarding both sustainable and efficient urban transport development, especially in developing cities facing numerous difficulties and challenges, a new backcasting approach with synthesized forecasting techniques has been established by Feng (2009). In this backcasting analysis framework, the integrated travel demand model developed by Feng et al. (2009) is applied to study urban and transport planning policies regarding traffic emissions from the perspective of environmental protection. Moreover, from the viewpoint of sustainable growth of a developing city, the Stochastic Frontier Analysis (Kumbhakar and Lovell 2000) has been adopted to analyze further the environmental efficiency of primary alternatives that satisfy basic traffic emission control targets. Following the proposed backcasting approach, a sustainable path can be found for the environmentally efficient urban transport evolution of Jabodetabek from 2002 to 2050. This path consists of CCD with construction of new roads and uncontrolled household growth from 2002 to 2020, PCD controlling increases in the number of households from 2020 to 2030, TOD with controls on the rise in the number of households from 2030 to 2040, and further PCD, controlling increases in the number of households from 2040 to 2050. This backcasting analysis of the Jabodetabek case confirms that such an approach can offer a practical and reasonable method of

studying and informing the urban transport development of a developing city in a more environmentally friendly manner. However, this backcasting analysis framework is not perfect. Because the abandoned subpaths for a given planning period are unconnected with the results of the policy applications in the next period, the backcasting framework cannot absolutely ensure that the decided path will optimize urban transport development. This shortcoming needs further improvement in future research.

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Chapter 4
Integrated Policy Analysis of Sustainable Urban and Transportation Development

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Abstract Sustainable urban and transportation development needs to balance economic sustainability, environmental sustainability, and social equity. This study conducts integrated policy analyses by explicitly incorporating these sustainability goals and optimizing the performance of transportation networks. This is done based on a bi-level programming approach, in which the upper level addresses sustainability goals and the lower level describes the optimization of a transportation network. On the upper level, car ownership, number of trips according to travel mode and accessibility-based social equity are optimized under the constraint of environmental capacity, which is calculated based on stochastic frontier analysis. On the lower level, a four-step travel demand modeling framework is adopted. In case studies, the maximal mobility level under the environmental capacity constraint is calculated, and various package policies for sustainable development are simulated.

Keywords Bi-level programming • Environmental capacity • Multiple criteria • Social equity • Sustainability targets

4.1 Issues of Sustainable Transportation Development

In the development process of transportation systems, there is always a paradox between progress in motorization and debate over the relation between various global problems such as traffic congestion, road safety, fuel consumption and environmental

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pollution. Transport problems have many basic potential causes. Recognized causes are infeasible or unbalanced development, such as the unlimited extension of urban areas, inordinate land use, and inadequate construction of road networks and overuse of private passenger cars. Each of these causes may involve multiple issues, and any positive change could improve the whole transportation system.

It is well known that most policy addressing various transportation problems should be framed within the concept of sustainable development, with the basic concepts of continued economy development, decreased environmental pollution, and a feasible level of social equity. Measures of environmental problems, regarded as key indicators in the construction of sustainable transportation systems, have been the object of attention by many researchers and policy makers in a wide range of areas, especially in recent years. Environmental pollution caused by road traffic is mostly responsible for urban pollution in most developed cities. Transportation development plays an important role in achieving the goal of economic progress and in the consequent environmental degradation in some developing countries. There are many studies showing that increasing traffic emissions are responsible for urban air pollution in various cities of the world. In Britain, at least three-quarters of CO, one-quarter of CO_2 and more than one-half of NO_x emissions are from car traffic (Stead 1999). A similar situation has appeared in most Chinese cities, where it is estimated that about 60 % of CO, 50 % of NO_x and 30 % of HC emissions are caused by car traffic (Li et al. 2001).

To control air pollution from motor vehicles effectively, one promising option is to adopt advanced technology and substitute fuels currently being developed for automotive engines. The application of new technology can alleviate emission levels to some extent, but there remains scope for practical application of this technology. Therefore, transport planners generally emphasize a range of control policies, such as taxation, road pricing, parking fees, and car sharing, to control the use of private passenger cars and consequently to reduce environmental pollution. Other arguments tend to address mode choice composition, whereby increasing the proportion of people choosing public travel could alleviate pressure on the environment. In addition, some policy sets, including road network design, planning patterns of land use, compact cities, and transit-oriented development, have been proposed.

It is generally acknowledged that ownership of cars, which cause heavy air pollution, is mostly responsible for urban transport environmental load. Given the requirement for economic development in developing countries, the increasing desire for private car ownership and car travel demand will continue in the future.

In fact, increase in rates of car ownership, which is inherently affected by consumer preferences, is inevitably restricted by various factors such as household income, taxation, available parking space and charges, road capacity, and environmental policies. Specifically taking into account the ever-increasing environmental impact of car traffic, environmental load should be kept within a certain threshold, called environmental capacity (EC), to achieve environmentally sustainable development. Therefore, it seems important to know the feasible level of car ownership in terms of EC to provide a reference point for policies.

If we examine the environmental issue from the viewpoint of policy making, one environmentally friendly alternative is to persuade people to travel by public transport instead of by private car. In other words, policies that maintain a desirable balance between private and public travel modes (called trip balance in this study) should be promoted. This has been an important measure in reducing the high ratio of car travel in developed countries and the increasing desire for passenger cars in developing countries. For this purpose, it is necessary to clarify the interaction between environmental load and mobility development, including the issues of car ownership and trip balance. To be specific, it is necessary to design an integrated model to specify the optimal level of mobility change considering environmental limitations.

Therefore, a crucial issue is to clarify the aforementioned EC. It is difficult to give an accurate definition of EC, and there is no widely accepted definition. However, we understand that EC refers to the level of environmental emissions (e.g., NO_x, SO_x and CO) that a city or a region can accommodate. The level of EC may be influenced by various factors. Some factors can be easily observed (e.g., green space, meteorological situation or geography), while other factors may not be observable (e.g., motivation for proenvironmental behavior and future technological innovation). In this sense, measuring the EC is still an unsolved problem. In reality, standards of air quality in a city are often adopted as a threshold for evaluating pollution levels. Other related long-term environmental considerations often rely greatly on expert opinions, which are sometimes arbitrary and lack theoretical support.

4.2 Objectives

This research intends to contribute to the construction of a comprehensive transportation system with a view to achieving environmental sustainability. Specifically, we propose an integrated modeling framework that addresses the optimization of total car ownership and number of trips in the context of EC. The model is constructed by a bi-level programming approach in which the two-level problem is illustrated by setting two optimization objectives accompanied by different decision variables that interact. On the upper level, the maximum of the mobility indicator, which incorporates total car ownership and total number of trips by private and public travel modes, is set as the objective function. The lower-level problem is a transport modeling process that captures route choice behavior when there are performance changes in network flow. The EC here is a constraint in the upper-level problem where the total emissions in zones or concentrations at roadsides are not permitted to exceed the relevant environmental capacities (i.e., frontier emissions or standards of air quality).

This proposed model is actually an integrated combination of multiple essential models that involve many aspects of the topic, such as system efficiency analysis, estimation of pollutant concentration, a modal split model, and traffic assignment. The research objectives are as follows.

- Evaluate the pollutant concentration on roadsides within cities.
- Measure the environmental efficiency and fuel consumption efficiency of transportation systems for various firms.
- Incorporate the general cost of fuel consumption in traffic assignment procedures.
- Obtain the maximum level of car ownership under the constraints of pollutant concentration on links and emission limits in cities.

- Obtain the maximum car ownership level and balance of number of trips between private and public modes under the consideration of EC in zone level.
- Evaluate the accessibility-based equity measures adopted under certain policies, such as road network improvement.
- Evaluate the performance of the model under different policy assumptions and analyze its sensitivity to future situations.

4.3 Representing Sustainable Development Goals

4.3.1 Maximum Mobility Level Under the Constraint of Environmental Capacity

Travel is a demand derived from participation in activities. In this sense, transportation accessibility is critical for people's quality of life, and policy makers are required to exert their greatest efforts to meet people's various mobility needs. From the individual perspective, owning a passenger car may provide the most convenient mobility tool for daily lives. At the same time, non-car travel modes can also provide necessary mobility for individuals without cars.

Normally, the number of passenger cars in a city is affected not only by people's preferences and income levels, and car attributes but also by circumstantial factors such as available parking space, road capacity, taxation and environmental policies. Therefore, increases in car ownership are not unlimited. Before traffic environmental load reaches the environmental capacity—that is, the maximum capacity for environmental pollutants—authorities must take measures to improve environmental quality, such as control of both vehicle ownership and use, and provide alternative non-car travel modes. Among varieties of environmentally friendly policies, emphasis is often placed on setting limits on car use rather than on ownership. This may be because of the negative impacts of car ownership control policies on economic activities, because the automobile industry is an increasingly important sector of the economy in developing countries. Moreover, automobile makers in developed countries have been attracted by the potential market and cheap skilled human resources in developing countries and have begun on-site automobile production to meet both domestic and international demand. Considering the ever-increasing environmental impact of road traffic, emissions from passenger cars, trucks and motorcycles should be controlled below a certain threshold, EC, to realize sustainable development.

Not everyone can own a car, and no one can own a car forever. Some people are not allowed to own cars because of age requirements (e.g., students under high school age). Some elderly people must relinquish their cars because of physical inability. Non-car travel modes are therefore needed. In this sense, a variety of travel modes (e.g., private and public travel modes) should be balanced in transportation systems.

Given the above information, mobility Y as a whole can be defined by distinguishing between two elements, as shown below:

$$\text{Mobility level}: Y = f(c_i, q_{ij}^m(c_i) \mid i \in I, j \in J, m \in M) \tag{4.1}$$

where c_i indicates the level of car ownership in zone i ($i \in I$), and q_{ij}^m refers to the demand for trips in travel mode m ($m \in M$) between zones i and j.

Mobility level Y as defined above can be regarded as a proxy for economic sustainability and should be maximized under the constraints of environmental capacity, which represents environmental sustainability. In other words, total traffic emissions cannot exceed environmental capacity. Considering the importance of environmental management, such constraints should be reflected at particular spatial levels (e.g., zone level). Note that q_{ij}^m is also a function of vehicle ownership, c_i.

4.3.2 Equity Measures

In sustainable urban and transportation development, equity issues should be regarded as having the same importance as economically sustainable progress and environmental conservation (Feitelson 2002). In recent years, both academic research and practical applications for transportation equity have been proposed. Transportation practitioners in the United States, for example, have been advised to avoid disproportionate adverse impacts on minority and low-income groups and to mitigate such impacts when possible. Regarding the concept of transportation equity, Yang and Zhang (2002) pointed out that equity can generally be classified into either social or spatial perspectives. Social equity basically refers to differences in income or social welfare between individuals or certain population groups. It can be considered the fairness or justice of the distribution of impacts (both benefits and costs) of an action on two or more subgroups (Litman 2007). Spatial equity commonly indicates the distribution of levels of transportation services (e.g., in terms of travel time, cost, distance, and number of transfers) between locations according to travel modes. Because distribution level is dependent on the state of traffic on the road network, the network design problem plays a central role in the assessment of spatial equity. Because of the increasing importance of the distributed impact of transportation policies, some researchers (e.g., Santos et al. 2008; Zhang et al. 2005; Connors, et al. 2005) have attempted to apply the formal indicators that are common in evaluating poverty and social welfare to evaluate transportation equity. The primary concern of such measurement is to represent differences in impact resulting from policy interventions across the entire transportation network. Although several functional forms are available, their performance and implications in measuring spatial equity have not been sufficiently addressed.

Because accessibility is one of the most important measures of urban and transportation systems, it is used in this study to define equity. In general, accessibility can be defined at either the individual or the zone level. Individual-based accessibility concerns the opportunity to participate in an activity or a set of activities that an individual at a given location possesses (e.g., Odoki et al. 2001). Effects of spatial, temporal, and interpersonal constraints on accessibility can be evaluated accurately based on individual accessibility, and accessibility can therefore be used to evaluate a wide range of policies. For the current study, it would be more practical to adopt a conventional location-based accessibility measure. This type of accessibility has been commonly applied in zone-based travel demand analyses based on gravity-type trip distribution models.

Spatial equity must be measured in a manner that reflects the distribution of policy impacts. Because a variety of inequity indicators are common in different fields, this study selects six major ones, including the GINI coefficient (GINI), the Theil index (THEIL), the mean log deviation (LDEV), the relative mean deviation (RDEV), the coefficient of variation (COV) and the Atkinson index (ATK). These indicators reflect varying levels of dispersion of accessibility across space. A detailed formulation is provided by Feng and Zhang (2012).

The Atkinson index is a measure proposed by Atkinson (1983). The distinguishing feature of the Atkinson index is its ability to gauge movements or to emphasize changes in different segments of the distribution. Various types of equity can be captured by the Atkinson index. For example, the equity level can be strongly influenced by lower zonal accessibility, meaning that those zones with lower accessibility will be given higher weighting in policy decisions; trade-offs between lower and higher accessibility can be completely compensated for, and Nash-type equity can be reached.

Among all the indexes listed above, the GINI coefficient is probably the most common measure of dispersion of income and wealth distribution. It is defined as a ratio with value between 0 and 1. A lower GINI coefficient indicates a more equal distribution of accessibility, a goal that is implicit in evaluations of social welfare. A value of 0 indicates perfect equity, meaning that each zone has the same level of accessibility, whereas 1 corresponds to perfect inequity, indicating that only one zone has complete accessibility, while other zones have none.

The Theil index is also commonly used to measure income equity. In fact, the Theil index and the mean log deviation are two special cases of the general entropy (GE) model (Theil 1967).

Relative mean deviation and coefficient of variation are two statistical evaluation indicators that are generally used to clarify distributional dispersion (represented as the deviation from the average level). They are both within the range from 0 to 1, with zero as the situation with no difference across distributions. High values indicate low levels of equity.

The concept of accessibility-based equity means that the dispersion of accessibility across zones should be fair. Without considering differences in distributional emphases, the ideal state is that the accessibilities in all zones are equal, indicating that people in any zone can access their destinations with the same level of transport service. Note that the concept of accessibility-based equity in measuring spatial dispersion can be easily generalized to other situations. For instance, the popularity of compact city planning and transit-oriented development (TOD) in practice suggests the rationality of spatially skewed distribution of accessibility. The compact city concept attaches the greatest importance to accessibility in central urban areas, while TOD is imposed on areas along transit lines. To accommodate such spatially skewed accessibility, distributional variations need to be captured with weighted importance. Accessibility in areas with high residential density should be given more emphasis than scattered areas.

The (in)equity indicators defined above should be minimized, which is also required to consider the influence of environmental capacity. With the above measures, social sustainability can be reflected in a quantitative manner in the planning process.

4.4 Conceptual Framework of Integrated Models

To construct a comprehensive urban transportation system with environmental sustainability, the mobility level and spatial inequity described above should be optimized under the constraints of environmental capacity to realize sustainable development. Such sustainability should be the highest priority for any policy decisions. Moreover, transportation network supply and demand should be in an equilibrium state to maximize efficiency of supply. The above discussion suggests that sustainability goals and transportation network equilibrium should be concurrent. This can be achieved using a bi-level programming approach in which the two levels of problems are illustrated by two different optimization objectives accompanied by different decision variables, which interact. At the upper level, maximizing mobility and minimizing spatial inequity is set as the objective function. The lower-level problem is a transportation network optimization model. Various user equilibrium (UE) assignment models may be used, such as fixed demand, variable demand and stochastic demand assignment models.

The details of the suggested integrated model are illustrated conceptually in Fig. 4.1. There are several major modules in this framework, including sustainable targets, environmental load, environmental capacity, database and policy set, and several models that were developed for this framework. The overall framework was developed based on the bi-level programming approach whereby the upper level is an optimization model with one, two or more sustainable targets with the constraint that environmental load is less than corresponding environmental capacity, and the lower level is a traffic assignment procedure. For details of the bi-level modeling formulation, refer to Feng et al. (2008, 2010).

At the beginning of this integrated model, OD (origin–destination) trip demand is assigned on the network using the combined trip distribution/assignment model, taking link emission and pollutant concentration as the outputs. Regarded as a restriction condition, the environmental load defined on a certain range is compared with environmental capacity. If the condition is not satisfied, a new variable of car ownership can be calculated based on the optimization model on the upper level because the single decision variable here is car ownership. After that, the calculated zonal car ownership will be used to estimate zonal mode choice by means of an aggregate logit-type modal split model. The mode choice results will induce changes in vehicular trips between OD pairs.

As a consequence, the new OD trip demand will be reassigned on the road network with the new environmental load as the output. Furthermore, the environmental load will be compared with environmental capacity to determine whether the restriction condition is satisfied. This calculation procedure will continue until the restriction condition is reached and the optimization of a sustainable target is obtained.

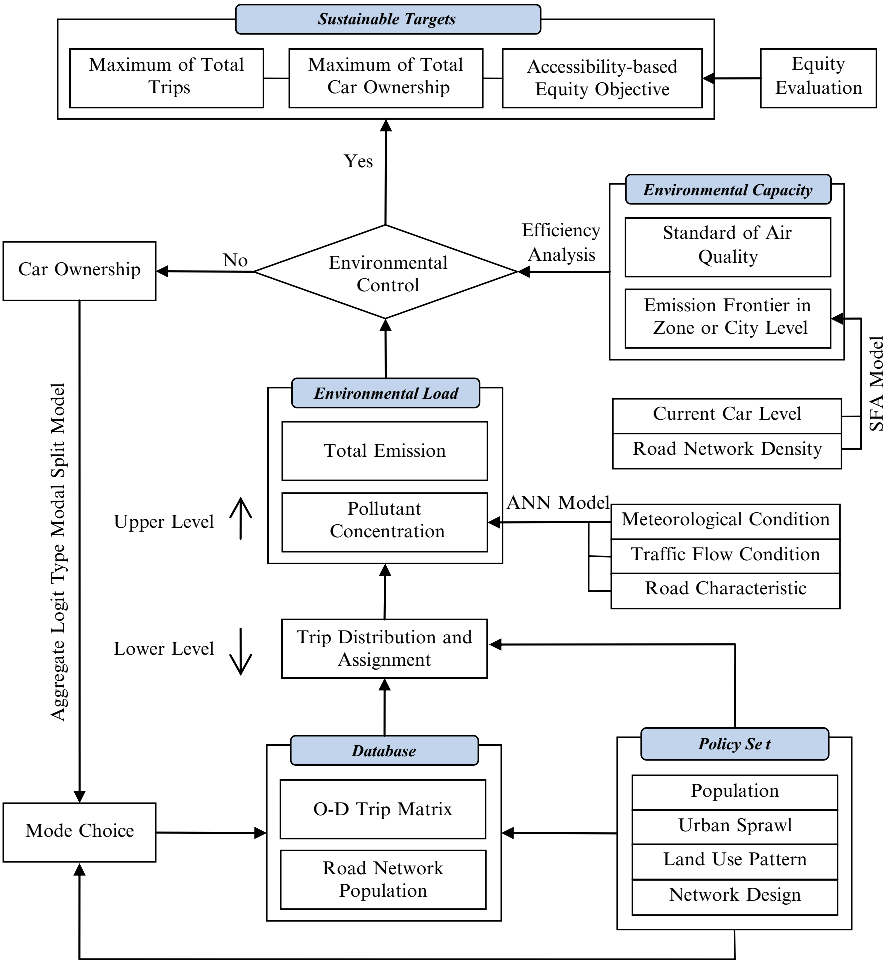

Fig. 4.1 Integrated modeling framework

The policy box embedded in this framework is to examine the sensitivity of this integrated model. The design of the policy set is constituted from the perspectives of population, urban sprawl, land-use patterns and network design. The policies can act in three areas: traffic assignment, mode choice and population distribution.

It should be mentioned that the equitable distribution of accessibility is considered to be a sustainability target. However, as the initial step, an equity evaluation study is conducted. Optimization incorporating an equity objective will be left for future study.

Several major contributions to previous research are made in this study. The most significant contribution is the proposed integrated modeling framework for the optimization of a comprehensive transportation system. The model can represent sustainability targets such as optimal level of car ownership, car use and equity simultaneously by taking into account environmental capacity as a limit. The bi-level approach adopted here represents both the optimal level of planned objectives and the effects of variations in network conditions. The outputs from this model are multiple, which may provide some meaningful reference points for policy making. In addition, the most promising contribution of this integrated model is the potential for further development and expansion that combining external models makes possible. Such integrated models are useful for examining various policies in combination by considering conflicts of policy decisions.

4.5 Forecasting Pollutant Concentrations on Roadsides

Forecasting of pollutant concentration is considered to be an important issue in analyses of environmental loads caused by road traffic. Pollutant concentration is usually influenced by various factors such as meteorological characteristics, weather conditions and traffic flow conditions, which have complicated nonlinear relationships. Therefore, it is difficult to describe the numerical relationship. In reality, policy makers' general concern is the pollutant concentration rather than the specific numerical relationship. However, it is still difficult to obtain a clearly accurate prediction of concentration, especially for road segments or cross sections. To tackle this issue, we developed a pollutant concentration forecasting model using an evolutionary artificial neural network (ANN) approach with genetic algorithms for roadside pollutant concentration (CO and CO_2) (Feng et al. 2006).

The relevant factors could be placed in three categories: meteorological conditions, traffic conditions and road spatial characteristics. Meteorological conditions are a main factor influencing pollutant dispersion. Pollutants in conditions of low humidity and high temperature can disperse much more quickly than in conditions of high humidity and low temperature; wind speed can also accelerate pollutant dispersion greatly. Moreover, wind direction has a strong influence on random changes of concentration. Traffic flow determines the amount of vehicular emissions, which indirectly influence air concentration. Many macro models for the calculation of vehicular emissions have been developed based on traffic volume and speed. In addition, the height of buildings near roads affects dispersion substantially. The narrower the roads and the taller the buildings, the more slowly the pollutants disperse. It is common in central urban areas for pollutant concentration on roads near a dense group of high-rise buildings to be much higher than elsewhere.

We confirmed the above model using a case study in Dalian City, China. For details, refer to Feng et al. (2006). The applicability of evolutionary neural networks was greatly improved with improvements in network design and the confirmation of other key parameters. Additionally, the forecasting accuracy of optimized neural networks is much easier to ensure than that of nonoptimized neural networks, is more easily available in pollutant concentration forecasting and has greater capabilities.

4.6 Environmental Capacity

To forecast pollution concentration, one of the crucial issues is to clarify the aforementioned EC. There is no widely accepted definition of EC, and the concept is generally difficult to define accurately. However, it is understood that EC refers to the maximal level of environmental emissions (e.g., NO_x, SO_x and CO) that a city or a region can accommodate to satisfy travelers' demand for mobility. Many factors affect the level of EC, some of which can be easily observed (e.g., green space, meteorological conditions and geography), while others may not be observable (e.g., motivation for proenvironmental behavior and future technological innovation). In reality, current air quality levels in a city are often adopted as thresholds for evaluating acceptable pollution levels. Other relevant long-term environmental considerations often rely greatly on expert opinions, which are sometimes arbitrary and lack theoretical support. Little research has been conducted on EC, and in this sense, measuring remains an unresolved problem requiring further investigation. Under such circumstances, the concept of "frontier," which has been widely applied in efficiency analyses in the field of econometrics, is adopted as a measure of EC. EC is defined as the emission frontier by assuming that there is no inefficiency in the transportation system. Regarding EC as the only limit for traffic emissions, this paper attempts to propose an integrated modeling framework that estimates the maximal mobility level; that is, the level of environmentally efficient car ownership and the number of trips by both private and public travel modes simultaneously, by explicitly incorporating transportation network performance and EC.

Vehicle ownership in a city is not unlimited. Before traffic environmental load reaches the maximum capacity for which environmental pollution can be accommodated, authorities must take steps to improve urban environmental quality, such as controlling both vehicle ownership and use. Thus, environmental capacity should be taken into account in the design of transportation systems. However, how to measure environmental capacity is still an unresolved problem because some influential factors are unobservable. Instead, current air quality levels in a city are often adopted as thresholds for evaluating acceptable pollution levels. Because air quality is expressed as the value of pollutant concentration, it can be easily used as a reference in the management of environmental load in spaces of any scale. In addition to environmental management at the level of transportation links, it is also necessary to reduce the total amount of emissions in the whole city from the perspective of environmental protection. Under such circumstances, we developed a multiple-output stochastic frontier model with flexible cause–effect structure. With this model, it is possible to calculate frontier emissions, namely environmental capacity, assuming that there is no inefficiency in transportation systems.

In system efficiency analysis, Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are the two dominant approaches. DEA does not impose a specific functional relationship between production output and input but estimates efficiency via an optimization formulation. One of the advantages of the DEA approach is that it can calculate efficiency even in cases of very small

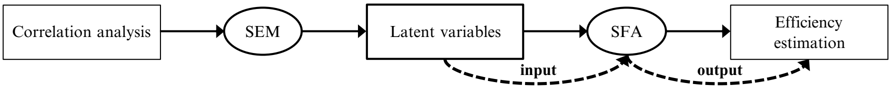

Fig. 4.2 Integrated model for system efficiency analysis

sample size, but its disadvantages are that the calculation results are very sensitive to the set of input variables. However, the SFA approach has the advantage of allowing for random shocks and measurement errors. It also assumes a specific statistical distribution of both random shocks and error terms. Because of the significant statistical characteristics of the SFA approach, as well as the sufficient sample size for parameter estimation and validation, it was chosen to calculate environmental efficiency in this study.

Both single-output and multiple-output SFA models assume that the inputs must be independent of each other. However, the choice of independent inputs for the model in real applications is quite difficult. An inappropriate set of inputs could cause a so-called multicollinearity issue, which results in wrong estimations and misleading interpretations of the results. To solve the problem properly, an SEM is adopted to generate new independent composite variables from the observed inputs, which may be interrelated. Composite variables here refer to latent variables. Needless to say, this is not the only reason to adopt the SEM. Another important reason is that the SEM can flexibly represent various cause–effect relationships among the observed and unobserved variables related to energy consumption in the transport sector. These variables could include information related to transportation systems and land-use patterns. This information on transportation systems is for both the demand and supply sides. After the SEM is estimated, independent latent variables directly related to energy consumption and system efficiency in the transport sector can be obtained and are consequently introduced into the SFA model as independent inputs (see Fig. 4.2).

The effectiveness of the above SFA model with flexible cause–effect structures was confirmed using the Millennium Cities Database compiled by the International Association for Public Transport (UITP) in collaboration with Murdoch University. The database includes data from 100 cities worldwide on demographics, economics, urban structures and a large quantity of transport data. Of particular significance for cities in developing countries, the source book contains a great deal of highly relevant information in the area of energy consumption, emissions and road traffic accidents.

In the empirical study, 77 cities were selected, and the results of inefficiency measures of the 77 cities are shown in Fig. 4.3, the five cities with the highest inefficiency scores being Shanghai, Beijing, Chennai, Jakarta and Mumbai, which are all in nonaffluent Asian countries, although they have almost the lowest levels of energy consumption and GDP. This implies that inefficiency is not always consistent with energy consumption. Comparing energy consumption in Africa with the relevant inefficiency levels, it is found that energy consumption is in inverse proportion to inefficiency. On the other hand, although energy consumption in North America,

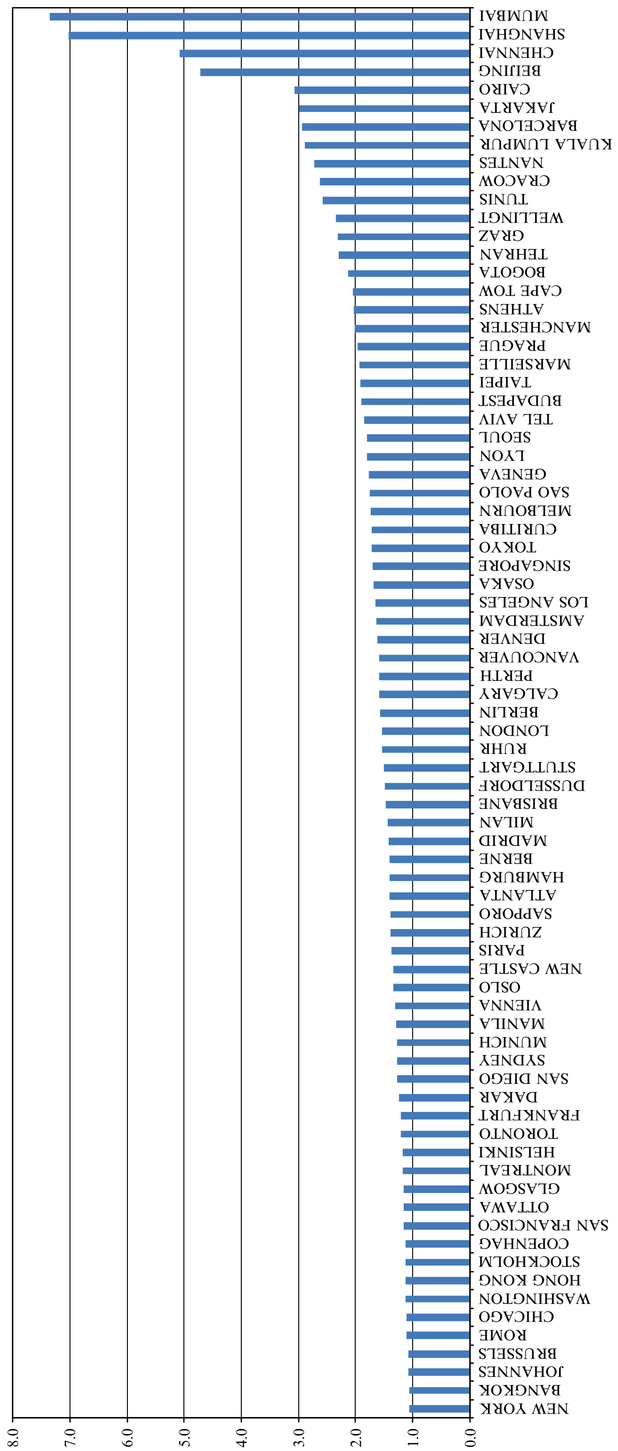

Fig. 4.3 Inefficiency measures of different cities (total: 77 cities)

Oceania and Western Europe differs, the differences in the corresponding inefficiency are not very large compared with those of Shanghai, Beijing, Chennai, Jakarta and Mumbai. It is also evident that the correlations between energy consumption and efficiency are inconsistent in different cities: some cities show positive correlations, others show negative correlations. For example, in North America and Oceania, although their energy consumption is clearly higher than that of other regions, the inefficiency levels are lower.

The calculated environmental frontier from the above inefficiency measures will be used to represent environmental capacity.

4.7 Applications

This section describes results and findings of the following three case studies: (1) measurement of environmentally sustainable mobility, (2) multiple-criteria evaluation of accessibility-based transportation equity in a road network design problem and (3) identification of policy packages for sustainable urban and transportation development.

4.7.1 Measurement of Environmentally Sustainable Mobility Level

1. Target City: Dalian, China
   Dalian City is located in the northeastern part of China. It is a mountainous city with car and bus as the major travel modes. There are almost no motorcycles and few bicycles in use, and more than 70 % of daily trips are served by public transport such as bus, light rail and trams. As one of the cities with the fastest economic development in China, Dalian has required substantial upgrading of both transport and road networks, especially in recent years. The number of private cars is increasing yearly, with an annual growth rate of almost 20 % (DMBS 2001–2005), which results in traffic problems such as congestion and environmental pollution. Figure 4.4 shows the road network in the central urban area of Dalian City. The road network, which is simplified for the sake of analysis, only includes 33 zones, 895 links and 544 nodes. The central area, which has dense road networks (gray lines), covers several zones such as 24, 25, 26 and 31. The region of zone 5 and its near northern part has become the second city center in recent years. Topological data from 2001 and personal trip (PT) survey data collected in 2004 were used in this case study.
2. Calculating Environmental Capacity
   The environmental capacity required for bi-level programming analysis is taken as the value at the zone level. That is, environmental capacity is reached when the transportation system of a zone performs most efficiently. Because cities such as

Fig. 4.4 Road network of central urban area of Dalian city in 2001

Dalian are still under development and are still not in an optimal state, this study proposes to measure capacity by comparing it with actual benchmarks (or best practices). For this purpose, SFA model estimation results based on the Millennium Cities Database (MCD) are used. One reason that we use this data is that some developed cities can be benchmarks for the inefficiency in Dalian. Another reason to adopt the MCD is that it is not possible to find benchmarks at the zone level within Dalian City. Specifically, we first calculate environmental capacity using the MCD and then measure capacity at the zone level in Dalian City.

3. Results of Calculation of Environmentally Sustainable Mobility Level
Our calculation results show that the maximal car ownership in Dalian city under the constraint of environmental capacity could be 1.5 times higher than the current level. Note that the maximum number of cars is calculated by assuming that the current population will remain unchanged. This assumption is made purely to evaluate the effects of environmental capacity. Figure 4.5 reveals that 19 of 33 zones could accommodate more cars within the environmental capacity than the current level, while in the other 14 zones, the current car ownership levels already exceed it. This suggests that car ownership levels in these 14 zones need to be reduced to meet zonal environmental capacity. Such findings

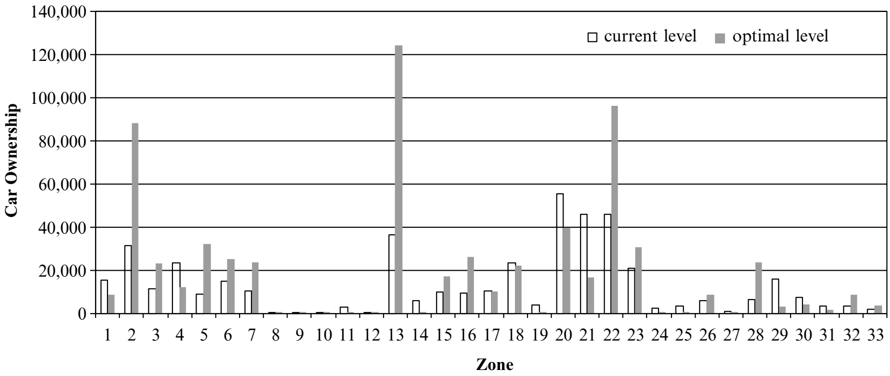

Fig. 4.5 Results of zonal car ownership

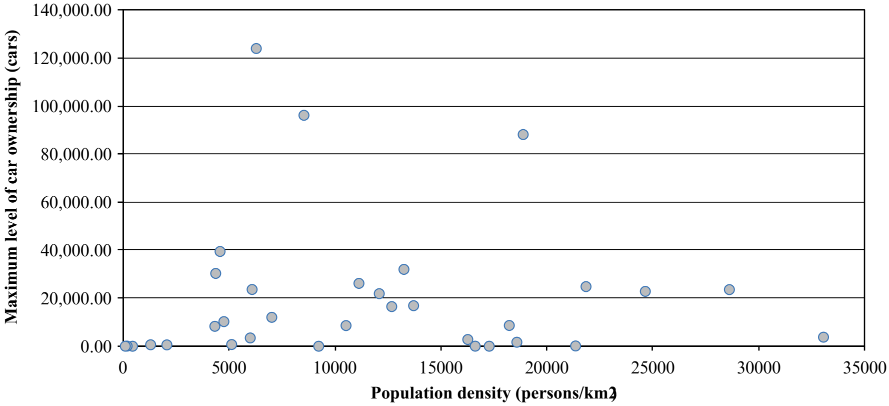

Fig. 4.6 Relationship between maximal car ownership level and population density

could provide a useful guide for policies in such areas as community-based transportation management. In addition, it is usually assumed/argued that increasing population density could reduce car dependence, but from Fig. 4.6, it seems that the maximal car ownership level has no clear relationship with population density. Our analysis results also confirm that population density does not influence the maximal share of car trips.

The final results of emissions relative to environmental capacities reveal that no zone has yet reached capacity (see Fig. 4.7). This differs from our original expectation that the maximal number of cars and trips by both private and public travel modes would be reached when zonal emissions reached their respective capacities. This is partly because of the nature of the optimization of an objective function where the total number of cars in a zone and total trips are used instead of zone number. Such objective functions do not ensure that emissions in each

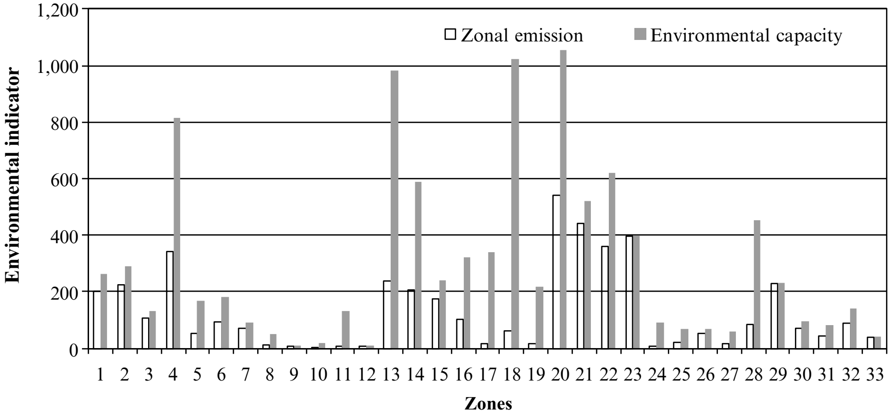

Fig. 4.7 Comparison between zonal emission and related environmental capacity

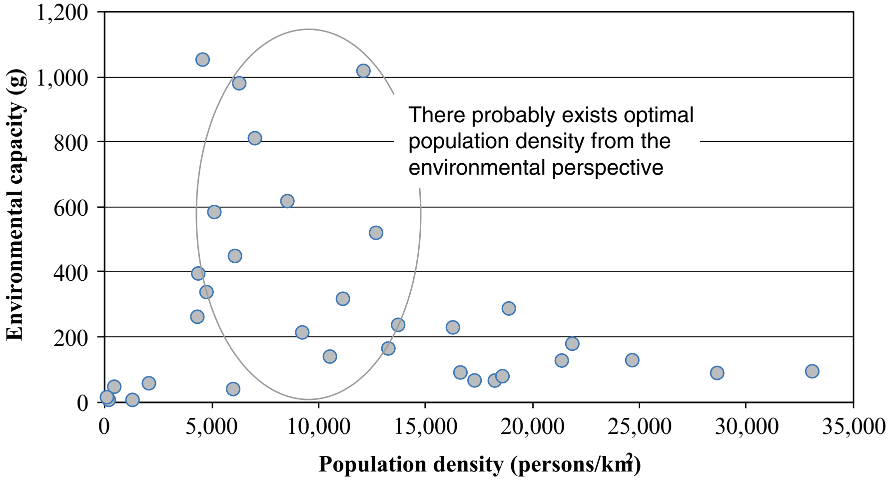

Fig. 4.8 Relationship between population density and environmental capacity

zone equal the zonal environmental capacity when the maximum number of car ownership and trips is calculated. Even if the emissions level reaches the zonal environmental capacity in each zone, increased car ownership in some zones could generate more trips, which would consequently lead to congestion and environmental pollution. Furthermore, unlike the situation for car ownership, it seems that there exists an optimal population density for accommodating the highest level of environmental emissions (see Fig. 4.8). This may be because higher population density leads to more efficient use of energy and consequently to greater environmental capacity.

4.7.2 Multiple-Criteria Evaluation of Accessibility-Based Transportation Equity

Road network design problems (NDPs) are discussed in this section. NDPs have been addressed in existing literature from a wide perspective, with the studies emphasizing the need for optimal design to mitigate possible externalities, such as traffic congestion and environmental emissions, in conjunction with road pricing or incentives. However, NDPs inherently address multiple objectives because of the sensitive characteristics of network performance and variations in travel behavior. This study investigates the performance of accessibility-based equity measurements in transportation and proposes a multiobjective optimization model to simulate trade-offs between equity maximization and cost minimization in network construction.

1. Target Road Network
   To investigate the performance of accessibility-based equity indicators and the efficacy of the proposed model, we conducted a numerical analysis using the Sioux Falls data, which were first gathered by Leblanc (1975). The data are from 24 zones, 24 nodes, and 76 links. The network depicted by Meng and Yang (2002) is shown in Fig. 4.9.

   The improved links are arbitrarily selected in advance along the horizontal line from nodes 12 to 18, passing through the links of 27, 29, 32, 33, 36, 48, 50, and 55. Because no population data are available in the original data set, zonal population is approximated in advance based on trip generation from the OD table. For the purpose of simulation, we assume that the links can be either improved or not improved, labeled 1 and 0, respectively. Improved links have a fixed level of capacity enhancement. To simplify, an assumption is made for the purpose of calculating construction cost that one unit of construction cost equals one unit of link capacity enhancement. Then the total cost of construction equals the total value of link capacity enhancement.
2. Sensitivity Analysis Under Different Network Improvement Scenarios
   The formulations of accessibility-based equity indicate that they may be sensitive to the patterns of network improvement that indirectly influence accessibility levels in zones. In this section, we check the sensitivity of these indicators from two perspectives: (1) assuming the same set of links but different capacity enhancement for one of the links (Case I) and (2) assuming a different set of links but the same total capacity enhancement (Case II).

   In Case I, we set two contexts according to the assigned links (in this case links 27 and 55) for network improvement scenarios. Links 32, 33 and 48 receive 1,000 pcu/h of capacity enhancement each, while other links receive no improvement. The two contexts demonstrate consistent performance according to different indicators. The values of all equity indicators, except for LDEV and RDEV, decrease as link capacity is enhanced. In addition, LDEV shows the same tendency as RDEV, resulting in a sudden increase when link capacity changes from 0 to 1,000 pcu/h.

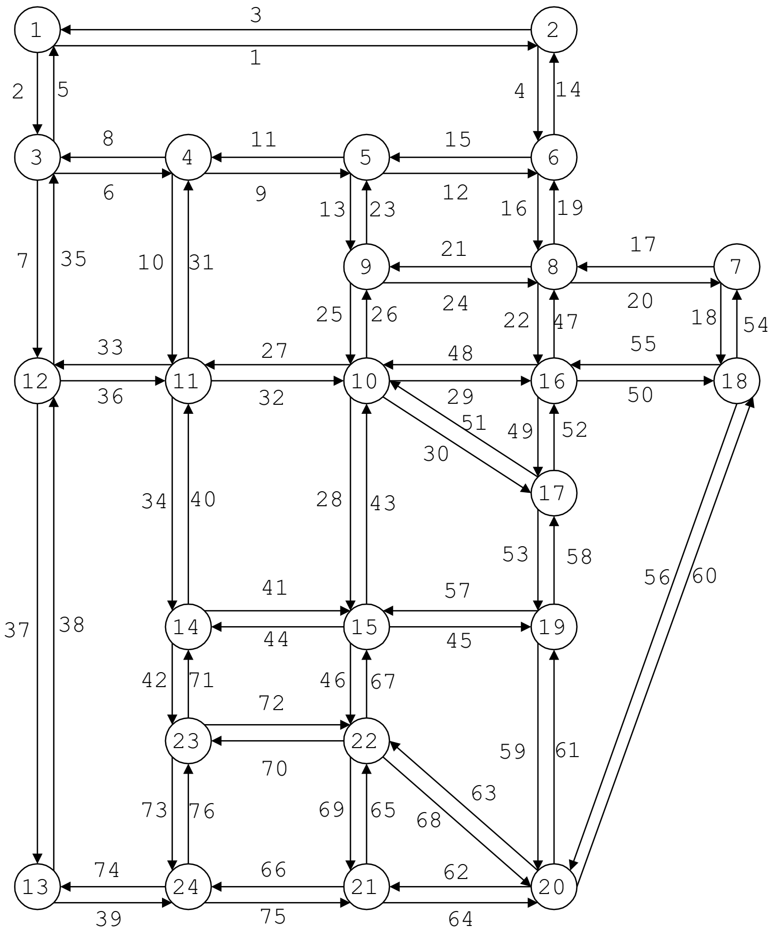

Fig. 4.9 Sioux falls network

Case II, which has the same total network improvement but a different set of links, is designed according to budget allocation for network improvement. We find that even with the same total degree of capacity enhancement, the resulting levels of equity are different. Values are sensitive to the specific links that receive capacity improvement. This is understandable from the perspective of network design, where network efficiency in general depends on the efficacy of link capacity improvement scenarios. We find that a feasible network design scenario should not only alleviate congestion but also balance spatial differences.

3. Trade-Offs Between Equity and Construction Cost
   In the proposed multiobjective model, a vector of the Pareto-optimal solution can provide multiple options for decision makers, especially when there are budget limitations on network investment. In general, the Pareto-optimal solutions are not unique and cannot be improved with respect to any objective without weakening performance with respect to other objectives. It is found that the scenario with the

highest total construction cost does not result in the highest level of equity for each indicator. This means that greater capacity enhancement would not always result in greater equity. There are multiple options for network improvement that can lead to the same level of equity. The best scenario depends on the number of improved links and the choice of links assigned for capacity enhancement.

4. Practical Implications

The above simulation results demonstrate that accessibility-based equity indicators are very sensitive measures of distributional differences across zones. This is mainly attributable to the nature of equity formulations with different weighting. To select the most feasible indicator, decision makers should be aware of the differences among these indicators. As revealed in the numerical example, LDEV and RDEV may behave in a similar manner, and the THEIL index may relate to high average accessibility when only equity maximization is considered. Indeed, the attempt to rank these indicators, which are defined differently, seems difficult and beyond the scope of this study. A thorough theoretical induction and comprehensive numerical analysis may be a positive contribution to future research.

In this study, accessibility is treated as a function of interzonal travel time and population of zones. It is evident that accessibility formulations will affect equity; accessibility at an individual level can represent vertical equity, with greater emphasis on social considerations. In the model, accessibility is calculated through a traffic assignment process. In long-term policy decision making, an average level of accessibility can be adopted. In contrast, for short-term applications, accessing accessibility-based equity needs to take the dynamics of network congestion into account. For example, a hierarchical scheme may be necessary for peak-hour and off-peak evaluations.

Although the proposed indicators are capable of measuring transport equity, they do not indicate how equitable the system is. In practice, it may be desirable to identify a feasible threshold to provide reference points for equity evaluations. For example, a society with income that has a GINI coefficient no larger than 0.2 is empirically treated as equitable. The distributional differences across zonal accessibilities may have specific characteristics that differ from the criteria used for income evaluation; sometimes they are even context specific. However, it is always true that the closer to zero the value is, the more equitable the accessibility distribution is.

4.7.3 Identification of Policy Packages For Sustainable Development

1. Scenario

Taking Dalian City as an example, we choose three groups of policies: population change (in terms of total population in a zone), urban sprawl, land-use pattern, and road network improvement. All the policies are represented in detail and combined to create diverse scenarios (policy packages). Different policies and combinations are shown in Table 4.1.

Table 4.1 List of package policies

Scenarios	S_0	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}
Population (+5 %)		√												
Population (+10 %)			√											
Population (+20 %)				√				√	√					√
Urban sprawl					√					√		√	√	
Land use change						√		√		√	√		√	√
Network improvement							√		√		√	√	√	√

Table 4.1 shows that three detailed policy scenarios of population change are assumed, where the population in each zone is assumed to increase by 5 %, 10 %, and 20 % respectively. Here, S_0 means the initial state with no policy consideration. The urban sprawl scenario is defined such that residents living in the central area of the city move to suburban areas because of high land prices The population in the central area will thus decrease (we assume a 30 % decrease). Conversely, the population in suburban areas will increase (we assume a 30 % increase). Some areas located between the city center and suburbs are assumed not to change in population. The change in land-use patterns is based upon the different functionalities of three types of land use: residential, industrial and commercial. Suburban areas attract a higher proportion of industry because land is cheaper. Commercial enterprises normally find central areas more profitable. A variety of residence types are assumed to be distributed in all zones. For the final scenario of network improvement, it is assumed that link capacities are all increased by 20 %.

The integrated model proposed in this study can certainly obtain a variety of outputs, such as the travel time, accessibility, level of service, and trip distance. However, a special concern in this study is the level of mobility and the corresponding environmental pollution. These are not only targets but also indicators used for evaluation. Therefore, we choose the results for total emissions and car ownership with respect to the scenarios.

2. Total Emissions

Results for total emissions are shown in Fig. 4.10. In this context, the scenario S_0 means the simulation result without policy considerations. The most effective policy for emission reduction revealed here is produced by S_7, where the population is increased by 20 % and land use is changed. This can be compared with the result of S_3, where only a 20 % population increase is considered. S_7 shows reduced emissions compared with S_4. This may indicate the importance of land-use planning in the process of population expansion. Because an increment to the population always means an increase in mobility, it may be possible to plan a feasible policy for land use that reduces the negative effects of mobility. In contrast, the result of S_6 reflects the most passive image. This result means that road network improvement cannot reduce environmental pollution. Furthermore, it may aggravate environmental load to some extent.

In addition, the amount of total emissions under scenario S_4, which assumes urban sprawl, is lower than that under S_0. This phenomenon contradicts the conventional view that urban sprawl increases fuel consumption and traffic emissions.

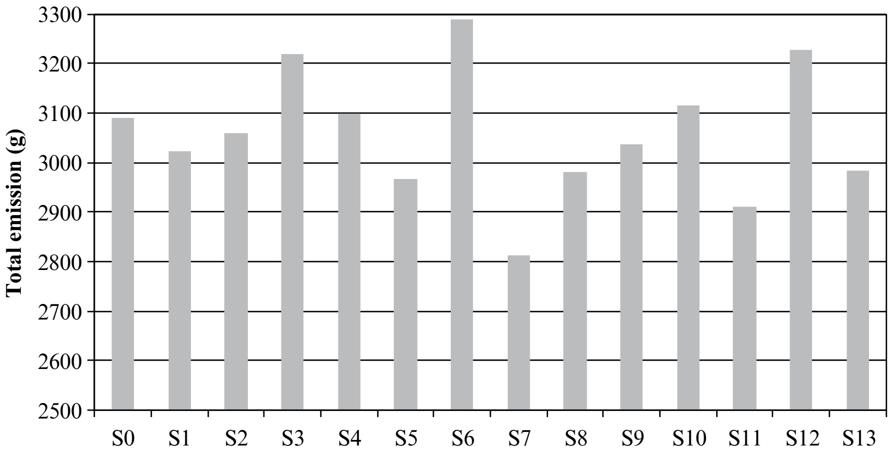

Fig. 4.10 Total emission estimated by different policy scenarios

Because environmental capacity considerations in zones limits travel through networks, travelers must take into account not only congestion but also environmental capacity. Limits on travel should receive policy support.

It should be noted that there is no significant correlation between population increases and total emissions (compare the results of S_0, S_1, S_2 and S_3). It is generally recognized that population increases always entail an increase in number of vehicles. This increases trip demand and consequently environmental pressure. However, under the current simulation framework, although the population increases in each zone, emissions caused by increased travel must be controlled within the threshold of zonal environmental capacity. This may also explain the result for S_4, where the population is sharply increased—a situation called urban sprawl. Population movement from central to suburban areas may increase total trip distance in the long term, which may cause additional pollution. However, the decreased emission results may reveal that the environmental load from the increased trip distance is much less than the emissions from congestion in the central area.

If we leave all scenarios unchanged with the exception of adding land-use change (S_5), a considerable alleviation of emissions can be obtained. However, when land-use policy is combined with the assumption of a 20 % population increase in each zone, total emissions increase greatly. One possible implication is that land use must be planned properly when the population is increasing rapidly. This also happens in S_9, S_{10}, S_{12} and S_{13} when a combined policy involving land-use planning is included. It may be that the combined policy set, including urban sprawl and network improvement, obtains some environmental benefit (S_{11}). However, the effect is weakened by including land use in the policy combination.

3. Zonal Emissions

Figure 4.11 shows the emissions level in each zone based on the estimations from various policy packages (scenarios). The most impressive evidence is that the zonal emissions level under different scenarios has a similar pattern with

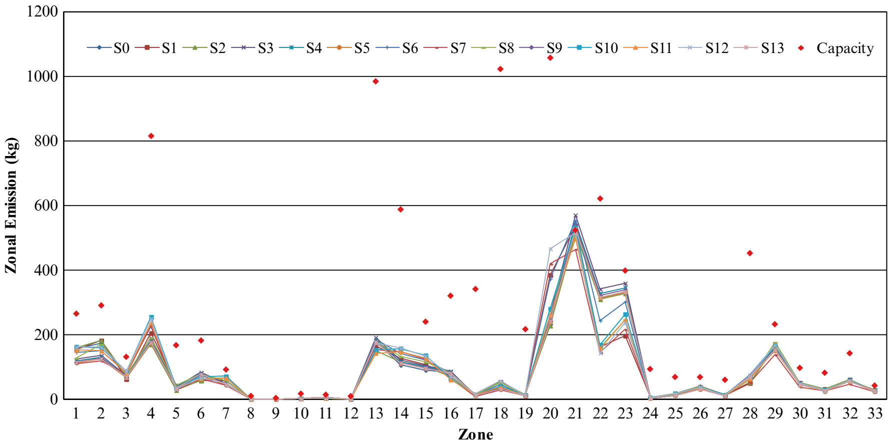

Fig. 4.11 Zonal emission of different scenarios and zonal environmental capacity (EC)

only slight differences in values. Because the emissions level in zones depends greatly on travel patterns, any changes in trip demand can affect emissions distribution. However, emissions are controlled at the zone level. When policies to increase the number of trips or car ownership in some zones are imposed, the environmental rule limits such an increase. In other words, the environmental capacity considered here mostly reduces the policy sensitivity of this model in the process of optimizing mobility control. Differences between the zones may still be found by comparing their emissions with their capacity.

4. Car Ownership

The results pertaining to maximum car ownership are shown in Fig. 4.12. A comparison of S_0, S_1, S_2, S_3 and S_4 indicates that car ownership levels do not change in proportion to population. Of the 13 policy scenarios, S_4 and S_{13} offer solutions closest to car ownership maximization, which indicates that these policies allow the highest levels of mobility given the need for environmental conservation. In addition, compared with S_0, land-use changes (S_5) also allow a significant increase in car ownership. Policy scenario S_6 produces a low level of car ownership, implying that that improved network capacity does not increase mobility when zonal emission is limited to zonal EC. Even when compared with S_0, when no policy is imposed, the maximum mobility associated with S_6 is smaller, suggesting that expansion of link capacity will not necessarily lead to environmentally friendly travel.

In S_4, with a sharp increase in population, a large number of passenger cars are needed to cope with daily travel demand. In addition, land-use change (S_5) also impels an increase in the total number of cars. This implies that land-use planning should avoid high dependence on car travel. As in the above discussion of a single policy network improvement (S_6), there is no positive effect on car ownership. Network improvement may attract more car travel but decrease

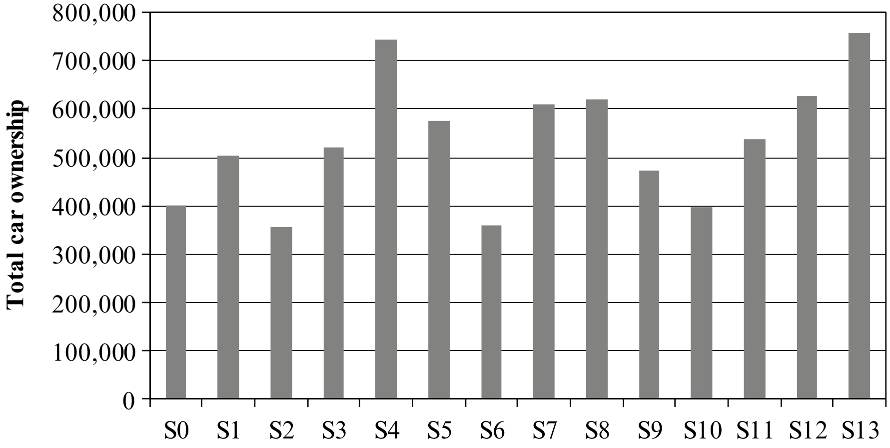

Fig. 4.12 Total car ownership estimated by different policy scenarios

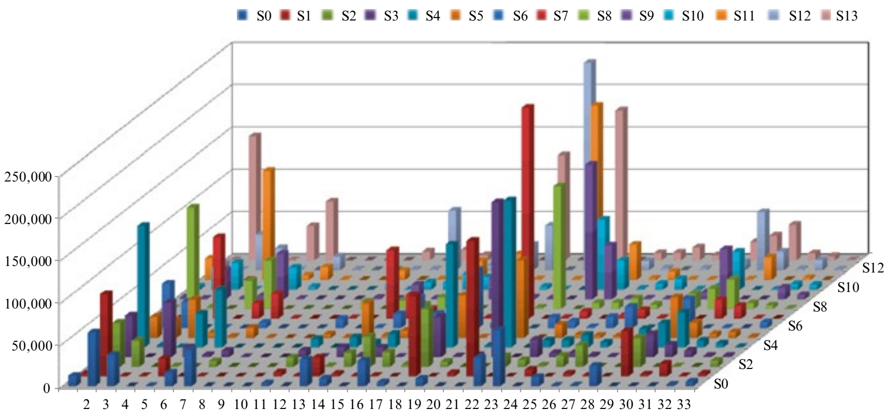

Fig. 4.13 Zonal car ownership for different policy scenarios

the maximum level of car ownership in terms of zonal environmental capacity. The policy combination of S_{13} is the most promising in terms of maximizing total car ownership and is identical to the result relating to total emissions.

Car ownership should be considered not only overall but also at the zone level. Figure 4.13 depicts the trend based on different policy assumptions. Some zones (8, 9 and 10) show a similar level of car ownership no matter which policy is given, and most zones obtain diverse results. This may be because of different policy assumptions. However, comparing car ownership in each zone is less important in this integrated simulation framework, and we shall not discuss it further.

4.8 Future Challenges

This research seeks to construct a simulation model for sustainable transportation; however, there are still many areas for improvement. Some significant improvement can be accomplished given time, but many theoretical, methodological and practical uncertainties remain. Based on this work, we mention two implications for future research.

The sustainability objectives discussed in this chapter incorporate mobility development and environmental issues simultaneously. This is not the whole story but one part of the work in the broad area of sustainable development. In fact, issues such as increasing concern for equity, pollution and environmental degradation can be included in this optimization system.

As an initial stage of the equity study, we conducted a comparative analysis of various equity measures in the context of road network design. The study involves a definition of equity that may differ from the traditional one. Because of variations in distribution over space, it can be said that absolute equity is not the ideal objective. Sustainable development from the perspective of fuel conservation and environmental improvement should include a relatively equitable distribution of accessibility, travel cost and level of service.

Therefore, future studies may take equity optimization as one objective. A combination of equity, total car ownership and number of trips is regarded as the overall optimal objective in the modeling framework. As a consequence, the integration of several objectives introduces the difficulty of balancing the final target by imposing various weights on each part.

The basic assumption of this chapter is that environmental pollution should not exceed corresponding environmental capacity. However, there are many constraints in real situations. Incorporation of more constraints could clarify the model but increase the complexity of simulation. One must consider which constraint is the most important and how to represent the importance of limitations in actual practice.

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Chapter 5
Interregional Tourism Demand and Destination Management

Makoto Tsukai and Makoto Okumura

Abstract The tourism market in Asian countries has grown rapidly every year, partially because of increasing household income and improvements in interregional transportation infrastructure. Analyses of nationwide tourism markets are, however, very limited because of a lack of data. Taking Japan as an example, this study evaluates the influence of improving interregional transportation infrastructure (including MAGLEV) on tourism demand in all the regions of Japan, focusing on trip generation, trip distribution, trip duration, and travel mode choice. Our analysis demonstrates the importance of the following destination management policies promoting regional tourism to different population groups: the integration of tourism resources among neighboring areas of major destinations, the policy of providing novel experiences to tourists from distant places, and coordination between transportation modes to encourage tourism.

Keywords Censored regression model • Destination management • Maximum sojourn time • Neighboring areas of tourist destinations • Tourism demand

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5.1 Introduction

5.1.1 Issues of Tourism Management

Tourism is one of the world's largest industries. In 2011, tourism contributed 9 % of global GDP and accounted for 255 million jobs. By 2022, one in every 10 jobs on the planet will be in the tourism industry (World Travel and Tourism Council 2012). The economic growth in developing Asian countries has stimulated demand for international tourism (Lym et al. 2008). In some developing countries, it is in fact the only viable means of stimulating development (Telfer and Sharpley 2008). However, tourism flows and patterns do not occur randomly. They are the result of not only a number of factors, including economic growth, cultural factors and access to transport, but also the activities of states, their policies and planning strategies and behaviors (Hall 2008). In the subject nation of this case study, the Japan Tourism Agency (JTA) was founded in 2008 to promote inbound tourism more effectively. The JTA is expected to integrate all tourism policy measures (including destination management and the improvement of transportation infrastructure) relating to tourist needs, safety, tourism industry development, and coordination of transportation, in addition to tourism resources, which were previously the responsibility of various sectors of the government.

The fundamental product of tourism is the destination experience. Although competition occurs between airlines, tour operators, hotels, and other tourism services, this interenterprise competition is dependent upon, and derived from, the choices of tourists between alternative destinations (Ritchie and Crouch 2000). In the context of transportation services, a recent controversy is the emergence of Low-cost Carrier (LCC) airlines. A large number of studies have focused on LCCs, hub-and-spoke network structure, airline alliances, or the competitiveness of LCCs compared with major carriers (Noran et al. 2001; Burghouwt et al. 2003). Fan (2006) reported differences in operating strategies between LCCs and major carriers in the EU region and concluded that LCCs have generally explored a new market, although it seems to be a niche, and the major gateways not only can maintain their usual flights but also can attract new direct services between local airports and others managed by LCCs. From the standpoint of local governments, sustainability of their own airports is a focal issue. Dennis (2005) examined the flight frequency of each airport to clarify the importance of airline networks and revealed that some limited airports attract more flights, while frequency of flights at medium-sized or small airports is diminished, and some effective alliances appear to be successful in the market. These studies suggest that local governments are required to establish innovative strategies in airport management based on a sound understanding of the local characteristics of all airports in the network.

Local government policy management also has difficulties on the demand side. Dresner (2006) pointed out the significance of the fact that that business passengers and tourists prefer different modes of travel. Compared with business passengers, tourism passengers tend to travel during the peak season because of the seasonality of tourist resources. This characteristic requires careful management of demand, because local tourism resources are often limited by “acceptable capacity” in terms of the number of visitors, especially in national parks or world heritage areas (Cawley and Gillmor 2007). It is widely recognized that excessive concentration of tourism demand not only harms the local environment but also discourages tourists from returning. To avoid “the tragedy of commons” (Hardin 1968) in a limited tourism resource, consistent regulation, incentive policies and cooperation among stakeholders in transportation, accommodation services, restaurants, retail, and local communities are very important. Adequate management of resources in tourism is a key issue in sustaining and developing local tourism industries (Limtanakool et al. 2006; Dwyer et al. 2009). Weng and Yang (2007) formulated a monopolistic competition model for the two-city system with various tourism resources and showed that the scale of economy in tourism investment concentrates resources, while a preference for variety drives the tourists to a diversity of areas. Their study also confirmed that lower transportation costs concentrate tourism demand in a limited number of destinations because of tourists’ preference for variety. In other words, each tourist destination requires strategies to differentiate it from others. Destination management strategies provide the foundation for successful destination marketing to attract tourists.

5.1.2 Tourists’ Decisions and Transportation Services

An interregional trip is characterized by low trip generation and long travel times with low-frequency transportation services on the route. When planning a trip, a tourist faces very complicated alternatives in the schedule: the set of destinations, the duration of the tour, transportation between destinations and the location of accommodation, which should also be considered. Hatzinger and Maxanec (2007) conducted a conjoint analysis of tour package choice based on a generalized log-linear model and found that the age of the traveler was the most important factor in determining not only the travel mode but also the destination choice, the total cost of the tour and the days spent at a destination. March and Woodside (2005) focused on the planned and revised schedule of interregional tourism and found that revised expenses and the days spent at the destination both exceeded the preliminary plan. It was also pointed out that the type of companions and experience on a past visit strongly influences tourist behavior. Nicolau and Mas (2008) examined tourist destination choice based on a stated preference survey and a random coefficient sequential choice model. It is revealed that destination choices that combine similar destinations and themes of trips chosen by tourists are preferred. In terms of tourist duration choice, Alegre and Pou (2006) estimated a model to count the days spent at a destination and demonstrated the importance of sociodemographic characteristics of tourists and characteristics of destinations.

Although there have been a large number of studies focusing on travel mode choice, time allocation and routing at destination (e.g., Bohler et al. 2006; Edy and

Molner 2002; Jara-Diaz et al. 2008), few studies focus on tourists' trip generation and preference for travel mode. Graham (2006) discussed the important factors that determine airline demand in tourism and reported that the purpose of tourism largely depends on the demographic characteristics of tourists. Tourists who cannot achieve the purpose of the trip through a ready-made package tour tend to make frequent trips of short duration. Anable and Gastersleben (2005) investigated the determinants of travel mode preference in tourism, focusing on the monetary cost and subjective evaluation (e.g., stress relief or relaxation). They reported that subjective evaluation of transportation mode has almost equal weight with LOS (level of service) on leisure trips. Wu et al. (2012) estimated Japanese tourists' choices in three stages—trip participation, destination choice and travel mode choice—but they ignored time-use behavior.

Jara-Diaz et al. (2008) empirically measured the value of leisure time, and in this study, the time allocation model derived by maximizing the utility of tourists under income and time resource constraints is calibrated. The estimated leisure time value is significantly higher for Europeans in terms of wage rates, while it is indifferent in the US case. Jara-Diaz et al. discussed why Europeans rate the value of leisure time more positively than Americans do. To investigate retirees' expectations regarding leisure and tourism, Nimorod (2008) conducted a semistructured interview survey of recently retired people in Southern US cities. Nimrod pointed out that retirees hoping to indulge a lifelong interest tend to pay more for transportation to reduce travel time. Heung et al. (2001) found that the purposes of travel for Japanese tourists are significantly different from those of other countries and that the importance of novelty, shopping and food is significantly different between genders or generations.

Transportation services in Japan have been greatly improved since an increase in the number of local airports on a long and narrow series of Japanese islands stimulated the interregional passenger travel market. While the *Shinkansen* high-speed railway network already operates in Japan, airlines are competitive with railways in OD pairs over 500 km apart, where they have an advantage in speed. In such situations, tourists have several alternatives for reaching a destination. Such a route consists of several modes. Given the constraints of holiday tourism, duration of stay at a destination is of critical interest to tourists. Substantial convenience is provided by rapid interregional transportation services such as local airports or the expressway network. Tsukai and Okumura (2006) devised a shortcut algorithm for calculating the round trip area (RTA) within a day and maximum sojourn time at a destination (MST). The calculated MST of each OD pair was regressed on the number of interregional airline passengers traveling for business purposes. The regression analysis shows that the calculated MST significantly influences the number of passengers. The important implication from Tsukai and Okumura (2006) is that improving transportation services does not always increase the number of passengers in all regions. Again, Weng and Yang (2007) already pointed out that lower transportation costs will both attract passengers from larger areas and divert passengers into rural areas. Okumura and Tsukai (2008) estimated an interregional tourism passenger model including MST and the number of tourism facilities as the attraction index of the destination, and at neighboring destinations. The estimated model showed that the MST parameter was positive, while some parameters of tourism facilities located near the destination were negative. Therefore, the complimentary and competitive effects of tourism resources in neighboring areas were observed simultaneously. However, the data set used in Okumura and Tsukai (2008) was the aggregated number of passengers. Therefore, the estimated model did not include any information about the demographic characteristics of tourists.

5.1.3 Objectives of This Study

The above overview of existing studies clarified several important unresolved issues. First, the fundamental product of tourism is destination experience (Ritchie and Crouch 2000); however, it has not been satisfactorily clarified whether a tourist prefers to visit destinations with similar or diverse tourism resources. One exception is the study by Zhang et al. (2009), who built a utility-maximizing time-use and expenditure behavior model based on a multilinear utility function incorporating attribute-based interdestination similarities and spatial structure of destination (defined by the closeness of a destination to other destinations). Tourism resources at a destination could include those at the destination as well as in the neighboring areas surrounding the destination. However, the study by Zhang et al. ignores the influence of tourism resources in the neighborhood of the destination. Second, because tourists need to return to their homes, their tourism decisions must be influenced by spatial and temporal constraints. However, these constraints have been poorly represented in the literature.

To address the above issue, this study first incorporates tourism resources both at the destination and in the local vicinity into the tourism demand model (i.e., trip generation and trip distribution models) and then proposes to introduce the concepts of RTA and MST at a destination into the model. Because tourists' trip generation and distribution are interdependent (Wu et al. 2012), such interdependence is reflected in the modeling process in this study. Specifically, we apply a censored simultaneous-equation regression analysis approach (Nelson 1977). Such an approach can help policy makers to identify opportunities for interregional collaboration in tourism resources. In addition, travel mode and tourism duration choices are also modeled. In this study, the trip generation/distribution model is estimated using the aggregated number of passengers as dependent variables, while travel mode choice and tourism duration choice models are estimated based on disaggregated data recorded at the level of individual travelers.

The remaining part of this chapter is organized as follows. The model for passenger demand analysis is formulated in Sect. 5.2, followed by a brief introduction of data in Sect. 5.3. The model estimation results are shown and discussed in Sect. 5.4. Section 5.5. reports the results of a simulation analysis. The study is concluded and policy implications are discussed in Sect. 5.6.

5.2 A Censored Regression Model with Heterogeneous Thresholds

If trip generation information is available for individual travelers, discrete choice models can be applied to predict the probability that each individual takes a trip. The total number of passengers in the population can then be calculated from probabilities weighted by expansion factors. If trip generation information is only available at the zonal level, the data set often includes zero observations. However, zero observations do not necessarily indicate that there is no trip between an origin and a destination, because the OD table is generated from a limited number of observations within a limited survey period. Therefore, the passenger demand model estimated from the data set omitting all zero observations—that is, including only positive observations—may be biased, because zero observations could simply indicate a considerably lower level of trip generation. To address this problem, Okumura and Tsukai (2008) proposed a new passenger demand model (a log-transformed gravity model) incorporating zero observations instead of discarding them. In their proposed method, the zero observations were first treated as censored at the lower bound of minimal observation criteria, and a Tobit model was then applied. However, it is not clear in their approach what factors should be introduced to explain the censoring phenomenon. To identify these factors to capture the censoring phenomenon, we adopt the following censored regression model with unobserved thresholds:

$$y_{1i} = \left\{ \sum_k \beta_k x_{ki} + \varepsilon_{1i} \;\; (y_{1i} \geq y_{2i}) 0 \qquad (y_{1i} < y_{2i}) \right. \tag{5.1}$$

$$y_{2i} = \sum_l \gamma_l z_{li} + \varepsilon_{2i} \tag{5.2}$$

where $i = 1, \ldots, N$ indicates the samples, y_{1i} is the observed dependent variable with error term ε_{1i}, and y_{2i} is the unobserved stochastic threshold that gives the lower bound of y_{1i} with error term ε_{2i}.

As shown in Eq. (5.1), y_{1i} is censored by y_{2i}. Moreover, x_{ki} and z_{li} are the observed variables that yield the expected values of y_{2i} and y_{1i}, respectively; β_k and γ_l are unknown parameters. For details of the model, refer to Nelson (1977).

Following Okumura and Tsukai (2008), we assume y_1 to be the log-transformed number of tourism passengers; x_{ki} is a log-transformed explanatory variable included in the gravity model (i.e., potential, attractiveness and impedance), and z_{li} is a variable used to explain the occurrence of "zero" observations (censored data). To simplify the discussion, all the estimates of γ_l are multiplied by -1 so that we can interpret a positive value of a variable to indicate an increase in the probability of trip generation, while a variable with a negative parameter indicates a decreased probability. This model is used to represent both trip generation and distribution.

Travel mode choice and tourism duration choice models are formulated using multinomial logit models (note that duration is categorized). Considering the choice mechanism in tourism, trip generation, travel mode choice and tourism duration choice may not be independent. It is therefore better to establish a joint model including all of the above choices. However, such joint models usually have a complicated model structure, which makes model estimation difficult, especially because no information is available about the order of choice decisions. Recognizing this difficulty, we first estimate the travel mode choice model and tourism duration choice model separately. To maintain consistency between the trip generation/distribution model, travel mode choice model, and tourism duration choice model, the samples are weighted by expansion factors. The estimated logsum values of the travel mode choice and tourism duration models are used as explanatory variables in the trip generation/distribution model.

5.3 Data

5.3.1 Net Passenger Traffic Survey and Tourism Resource Data

A difficulty in gathering interregional passenger trip characteristics to assess nationwide demand is conducting the survey. "Site-based surveys" at destinations are not easy to conduct in all areas and are inefficient at the point of origin ("home-based surveys"). An interregional "net" passenger traffic survey of Japan, however, was undertaken in 1990 and has been repeated every 5 years. This survey counts tourist passenger traffic at controlled sections and aggregates the data into the interregional OD tables. This survey captures individual characteristics of tours, such as origin and destination of each transportation mode on the entire route if travelers transfer. This survey covers all modes such as car, train, aircraft and ship between all the regions of Japan. However, the "gross" passenger traffic survey aggregated for each mode cannot capture transfer between the modes. The purpose of the net passenger traffic survey is to provide fundamental information for interregional transportation infrastructure planning. Each sample is assigned an expansion factor based on the gross number of travelers for each trip purpose or each transportation mode. The aggregated OD tables are available on the web site of the Ministry of Land, Transportation, Infrastructure and Tourism of Japan (MLTIT 2007). After the third survey in 2000, trip information at the individual level with the corresponding expansion factor became available. Interregional tourism passenger traffic data used in this study were extracted from car, train and aircraft passenger trip data on holidays when surveys were conducted in 2005. The published OD table records passenger trips between 207 areas of origin (residential areas) and (major) destinations. Note that this survey excluded the intrazonal trips in each prefecture and intraregional trips in the Tokyo, Nagoya and Osaka metropolitan areas, to omit short-distance trips. We used 194 of 207 areas, where the excluded areas are remote isolated islands.

Figure 5.1 shows the demographic characteristics of tourism passengers. Note that the samples are aggregated according to expansion factors. There were more male than female passengers. Figure 5.2 illustrates the relationship between travel mode and tourism duration. It is observed that public transportation passengers tend to spend more than 2 days at a destination, while over 80 % of car users finish the trip within a day. Figure 5.3 demonstrates the shares of transportation modes by trip distance. Car trips predominate within 300 km, the largest share of rail trips occurs between 300 km and 500 km (more than 60 %), and the largest share of air trips occurs over 500 km (more than 60 %).

The database of regional tourism resources and demographic characteristics was compiled from national statistics, or from the web site. The sources of data are summarized in Table 5.1. The last column shows the categories of data sources.

5.3.2 Calculation of Maximum Sojourn Time at Destination: Round Trips in a Day

Because information about the level of service for each passenger is not recorded in the net passenger traffic survey, we calculated it for each OD pair. An RTA based on an MST was obtained by repeatedly applying a route search among the targeted points of origin. However, the exact calculation of RTAs would require a huge amount of information on public transportation, such as departure/intermediate/destination nodes with times for all scheduled flights, trains, and access modes. This database is already included in some commercial base software, but extracting information from it is prohibited for copyright reasons, so the only available source for our study is paper-based timetables. Another difficulty in calculating an exact RTA is the quite large calculation for medium- to large-scale networks. In this study, we devise a feasible procedure to calculate the approximate MST and RTA based on a simplified database of interregional public transportation.

The outline of the procedure is summarized in Fig. 5.4. In this procedure, the *k*th path search algorithm is effectively used to ease calculation. The *k*th path search algorithm proposed by Kato et al. (1978) consists of the shortest path search using the Dijkstra algorithm, the second path search routine (FSP), and *k*th path search algorithm (KSP). This algorithm can sequentially search the paths from the shortest to the *k*th shortest between a pair of nodes. Because the original *k*th shortest path search algorithm is for nonarced networks, we improved it for an arced network as shown in Step 1 to 5. To shorten the process of calculation, our algorithm does not use all information about the timetable for each flight or train because transfer and waiting time for the next mode are not conveniently calculated in the search path. Instead, we set several discrete departure times from a point of origin and then check the frequency of entry to each link on the route to a destination. For this procedure, the frequency of each link is recorded for several time bands (i.e., time bands 1, 2 and 3 are between 6:00 and 9:00, between 9:00 and 12:00, and between

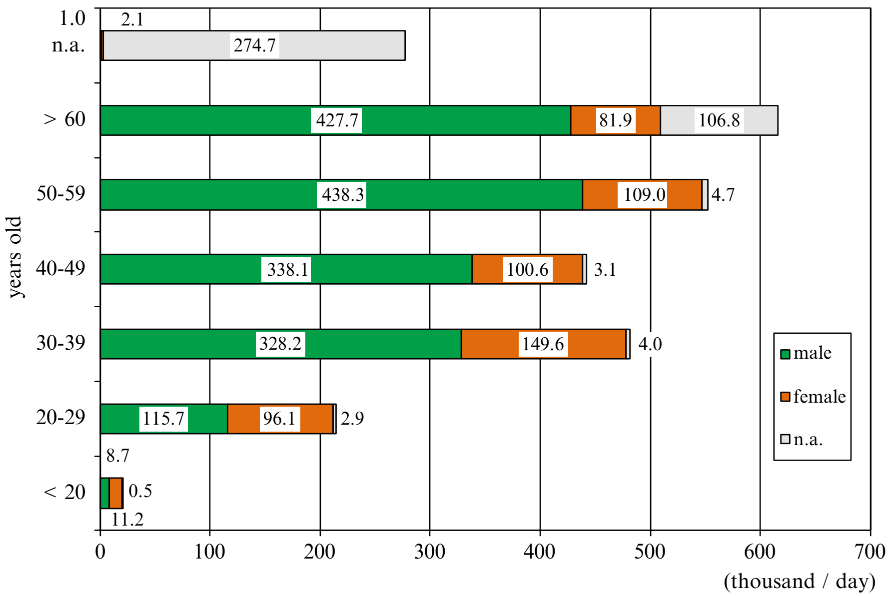

Fig. 5.1 Tourism trips by gender and age

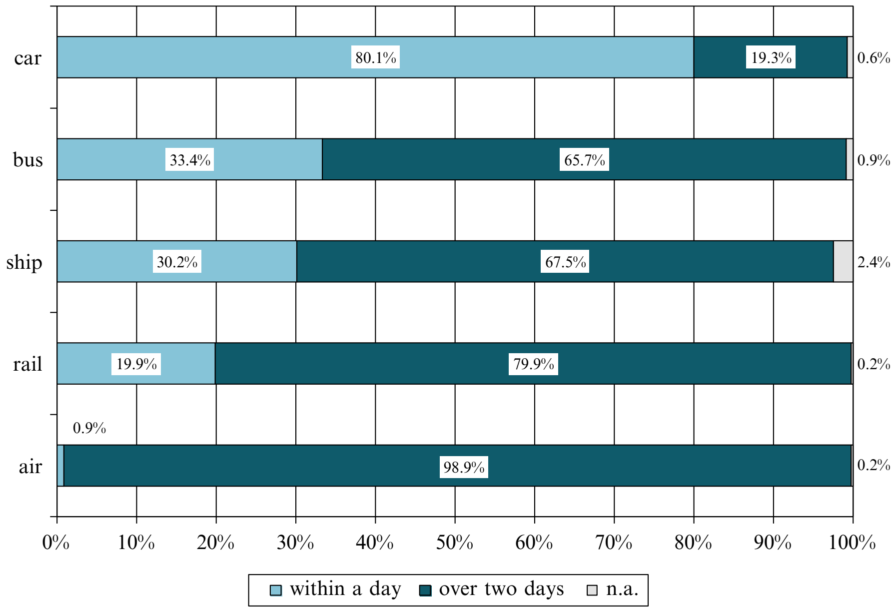

Fig. 5.2 Transportation modes and tourism duration

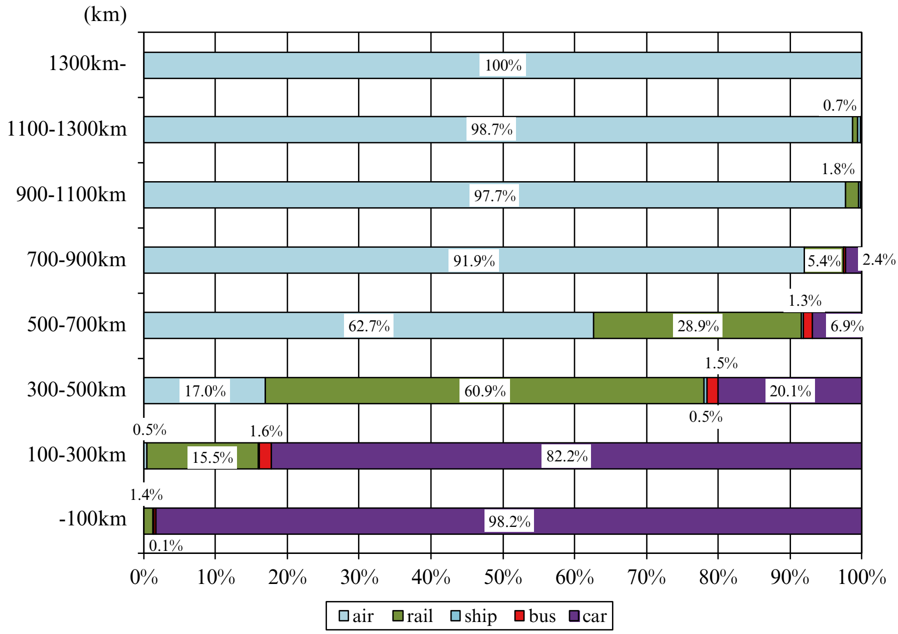

Fig. 5.3 Transportation modes and trip distance

Table 5.1 Summary of regional tourism resource

Variables	Data source	Category
Population	National census	(1)
Gender and generations		
Forest/developable area	Statistics in city and town (ASAHI news paper company "Minryoku")	(2)
Number of museum		
Famous hot spring	Ministry of the environment, bureau of national environment :annual report on hot spring http://www.env.go.jp/nature/ (last visited at 2009.1)	(3)
World heritage		(4)
National park		
Natural preserved area		
Disney land	The data base for regional tourism resource	
Hakkeijima	http://www.kankouchidokuri.jp/ (last visited at 2008.12)	
Theme park		
Traditional area		
Traditional buildings		

12:00 and 15:00, respectively). Figure 5.5 shows the frequency calculation for each link. Suppose a passenger goes by the kth shortest path between OD pair ij at departure time d. The mth link is a number of sequential links counted from the origin node i. The link frequency f_{ij}^{dkm} appears when the passenger departs from i to enter

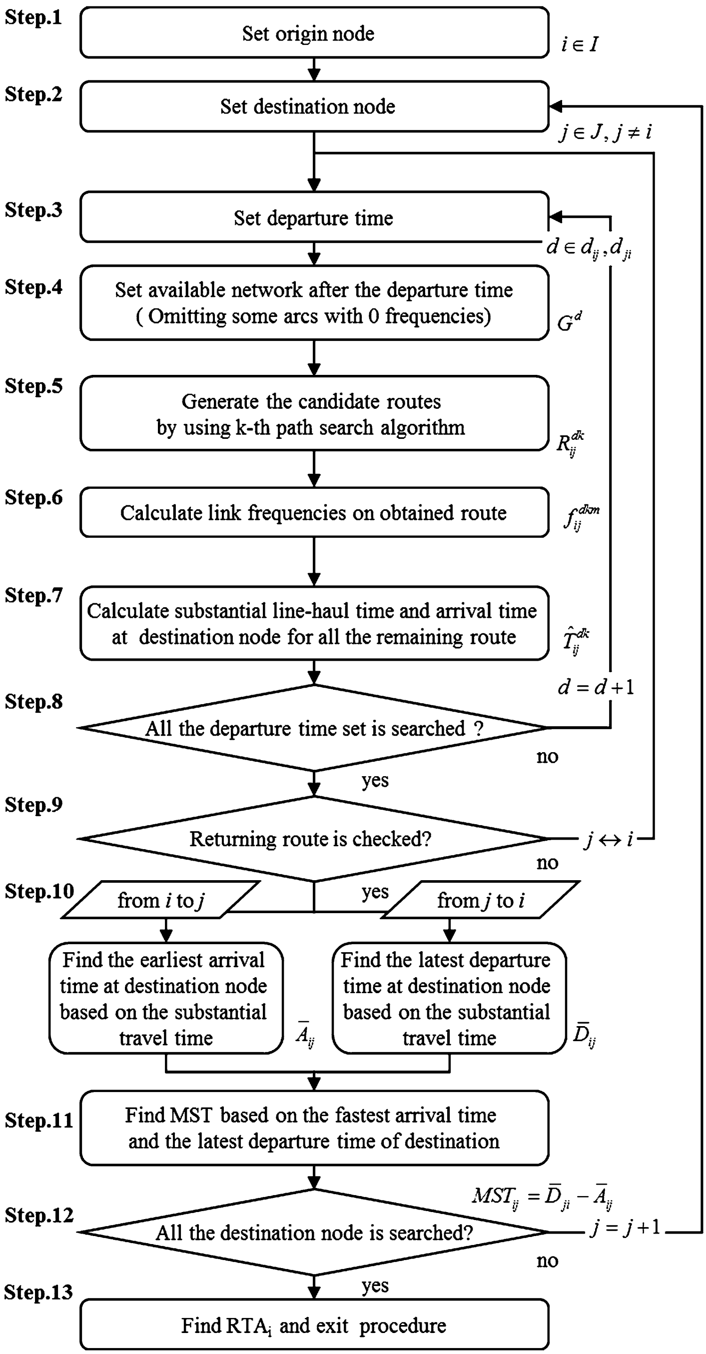

Fig. 5.4 MST (RTA) calculation procedures

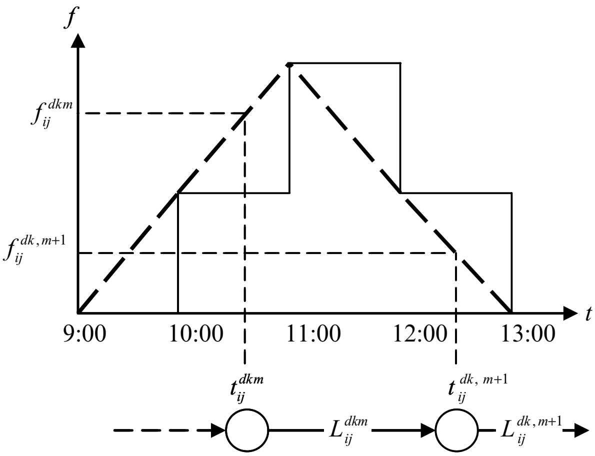

Fig. 5.5 Calculation image of link frequency based on the link entrance time

the link at t_{ij}^{dkm}. The frequency of a link on the route with departure time d is calculated by linear interpolation, according to the frequencies of previous or subsequent time bands. In Step 6, the lowest frequency on each generated route is calculated.

A substantial travel time $\hat{T}_{ij}^{d}$ and the earliest arrival or the latest departure time are defined in Eqs. (5.3)–(5.7) (corresponding to Step 7 to 10, respectively):

$$\hat{T}_{ij}^{d} = \min_{k}\left(\frac{1}{2}\cdot\frac{D}{\min_{m} f_{ij}^{dkm}} + T_{ij}^{dk}\right) \tag{5.3}$$

$$\bar{A}_{ij} = \min_{d}\left(T^{d} + \hat{T}_{ij}^{d}\right) \tag{5.4}$$

$$\bar{D}_{ji} = T^{d} \mid \max_{d}\left(T^{d} + \hat{T}_{ij}^{d}\right) < 24:00 \tag{5.5}$$

where D is a time band defined for frequency data, and T_{ij}^{dk} is the sum of link travel time along the route (excluding waiting time).

In this study, we assume that expected waiting time at a link with the lowest frequency is an index of route waiting time. Equation (5.5) means the round trip constraint that the arrival time on the returning trip should not exceed 24 h. The MST for each OD pair and the RTA for each origin node are calculated in Eqs. (5.6) and (5.7), respectively (corresponding to Step 11 to 13):

$$MST_{ij} = \bar{D}_{ji} - \bar{A}_{ij} \tag{5.6}$$

$$RTA_{i} = \left\{ j \mid MST_{ij} > 0 \right\} \tag{5.7}$$

Table 5.2 Tourism modal choice model

Explanatory variable		Estimate	*t*-value
Common	Fare (thousand yen)	−0.072**	−71.19
	Travel time (min)	−0.005**	−102.33
Air	Number of accompanied person	−0.163**	−88.71
Car	Number of accompanied person	0.005*	2.44
Rail	Constant	−2.107**	−191.24
Likelihood at initial		−126243.74	
Likelihood at convergence		−59902.75	
Rho squared, adjusted d.f.		0.525	
Number of samples		114,912	

Significant level: +: 10 %, *: 5 %, **: 1 %

where, $\bar{D}_{ji}$ and $\bar{A}_{ij}$ are the latest departure time at destination j to arrive at origin i up to 24:00, and the earliest arrival time at destination j departing after 6:00 at origin i, respectively.

A difficulty occurs in calculating the exact MST because it requires a timetable for trains, aircraft and ships that covers the whole of Japan. Tsukai and Okumura (2006) devised a shortcut procedure to calculate the approximate MST for all OD pairs. To calculate the MST and level of service for all OD pairs, an interregional network database was constructed to maintain correspondence with the areas in the interregional net passenger traffic survey. The dataset consists of 240 nodes with 501 links. The attributes of each link are travel time, frequency, and modal information (railway, airline, and access link). Frequency is recorded for every 3-h period, such as 6:00–9:00, 9:00–12:00, … , 21:00–24:00. Therefore, there are six periods for travel in one direction, so the frequency data set for a link has 12 attributes. The level of service of the timetable is assessed from a timetable published in November 2005. In this study, RTA is defined as the set of areas from which a person could return if departing after 6:00 and returning before 24:00.

5.4 Results of Model Estimation: Three Aspects of Tourism Demand

Table 5.2 shows the estimated parameters of the tourist travel mode choice model. The adjusted Rho-squared index is 0.525, suggesting a reasonably satisfactory level of model accuracy. As the level of service variables, fare and travel time are negative and significant. Number of accompanied people is negative and significant for choice utility of airlines but positive and significant for car choice.

Table 5.3 shows the estimated parameters of the tourist duration choice model. Model accuracy is sufficient in that the adjusted Rho-squared index is 0.728. Because MST has a nonlinear influence on tourism duration, dummy variables corresponding to each MST category are used as explanatory variables. Most MST

Table 5.3 Estimation results of tourism duration choice model

	Within a day		2 days		Over 3 days	
Explanatory variables	Estimate	*t*-value	Estimate	*t*-value	Estimate	*t*-value
MST below 2 h	−1.077**	−10.04				
MST from 2 to 4 h	−1.939**	−18.26				
MST from 4 to 6 h	−2.163**	−19.43				
MST from 6 to 8 h	−1.370**	−15.21				
MST from 8 to 10 h	−0.835**	−9.76				
MST from 10 to 12 h	−0.030	−0.34				
MST over 12 h	1.609**	17.92				
Teens and 20s (1)			0.764**	25.19	0.806**	11.13
Male from 30s to 50s (1)			−0.704**	−31.69	−0.709**	−13.25
Female from 30s to 50s (1)			0.264**	10.98	0.428**	7.25
Male over 60s (1)			−0.632**	−26.05	−0.049	−0.90
Female over 60s (1)			0.849**	24.71	1.583**	22.71
Hokkaido dummy			0.169**	5.69	−0.321**	−4.89
Tohoku dummy			−0.057+	−1.69	−0.391**	−7.70
Kanto dummy			0.610**	20.61	0.347**	8.66
Hokuriku dummy			−0.278**	−5.89	−1.428**	−15.72
Chubu dummy			0.339**	10.49	0.052	1.19
Kinki dummy			0.479**	14.21	0.400**	7.74
Shikoku dummy			−0.425**	−6.58	−0.367**	−3.28
Kyusyu dummy			−0.014	−0.46	−0.289**	−5.32
Number of museum at neig. of D (2)			0.000**	4.18	0.002**	15.60
Famous hot spring at neig. of D (3)			0.749**	40.03	0.503**	10.25
World heritage dummy at neig. of D (4)			0.178**	9.14	0.018	0.52
National park/natural pres. area dummy at neig. of D (4)			0.231**	16.53	0.112**	4.00
“Disney land” dummy at neig. of D (4)			−0.094**	−3.40	−0.346**	−8.66
Theme park dummy at neig. of D (4)			0.115**	4.82	0.503**	11.79
Traditional area dummy at neig. of D (4)			0.017	0.68	−0.040	−0.89
Traditional buid. dummy at neig. of D (4)			−0.032*	−2.05	0.059*	2.28
“Hakkeijima” dummy at neig. of D (4)			0.371**	12.63	0.524**	12.37
Seaside dummy at neig. of D			0.585**	45.14	0.619**	35.84
Difference in temp. |O-D| (2)			0.028**	6.97	0.027**	5.73
Difference in long. |O-D|			0.517**	37.71	0.889**	54.99
Constant			−2.911**	−29.65	−4.093**	−31.68
Likelihood at initial	−126243.74					
Likelihood at convergence	−34298.57					
Rho squared with adjusted d.f.	0.728					
Number of samples	114,912					

The marks with explanatory variable ((1) to (4)) correspond to the categories in Table 5.1
Significant level +: 10 %, *: 5 %, **: 1 %

categories of durations within a day are significant, but they are significant and negative below 10 h. Furthermore, they do not monotonically increase with MST. Tourists from a point of origin with 4–6 h MST tend not to take 1-day trips. Most of the composite variables of gender and generation for the duration alternatives of "2 days" and "over 3 days" are significant.

Because the number of respondents is small in the 10s and 20s age groups, they are grouped together. Concerning the demographics, women aged in their 30s to 50s and over 60 prefer longer durations of stay than other travelers. The parameters for trip destination areas (i.e., from Hokkaido to Kyusyu) are mostly significant. The parameters for Tohoku, Hokuriku, Shikoku and Kyusyu are negative, while those for Kanto, Kinki and Chubu, which have larger populations, are positive. Kinki and Kanto are the destinations where tourists prefer to stay for more than 3 days.

All the variables in this model are defined as tourism resources in the areas surrounding a destination under study. Introducing such information clarifies the contribution of these tourism resources to tourism demand in areas neighboring the destination. In this analysis, a "neighboring area" is defined as an area where MST is more than 12 h travel from the recorded destination (not from the origin). The results show that the destinations in the neighboring areas of famous hot springs, national parks or nature reserves, Hakkeijima in the Yokohama area or world heritage sites encourage longer stays, while the destinations neighboring Tokyo Disneyland encourage shorter stays. The absolute differences from origin in temperature and longitude between an origin and a destination significantly prolong the duration of travel as the differences increase, and they contribute more to trips over 3 days. Tourists prefer a longer stay if the difference in climate or geographical features is large.

Table 5.4 shows the estimated parameters of the tourist trip generation/distribution model, formulated as a sample selection model. Note that in this table, "O" and "D" denote the origin and the destination, respectively. The correlation coefficient for trip generation and that for the gravity model are quite high. In this model, the variables with positive parameters cause trip generation, and *vice versa*. Among the significant variables in the trip generation model, developable area (i.e., area that has tourism potential but is not currently developed) at the point of origin, famous hot springs at the point of origin, national parks, nature reserves, and traditional buildings are positive, while number of museums and world heritage areas are negative. Aggregated characteristics of gender and generation combinations show that females contribute to trip generation, except those in their 40s. The estimated parameters of population at the point of origin are positive, so the interregional trip generation rate is higher in areas with larger populations. The tendency of these signs of tourism resource parameters shows that tourism trips tend to be generated in rural regions, after adjustment for the population size of the point of origin.

Figure 5.6 shows the expected probability of tourism trip generation for each traveler, calculated from the trip generation model. The probability of tourism trip generation for each traveler is higher in the Hokkaido, Tohoku, Kanto, and Kyusyu areas. In the gravity model, the logsum parameters of travel mode and tourism duration choices are both positive and statistically significant. The parameters in the

Table 5.4 Estimation results of tourist trip generation/distribution model

	Trip generation model		Gravity model	
Explanatory variables	Estimate	*t*-value	Estimate	*t*-value
Log sum in transportation			1.093**	61.45
Log sum in schedule			0.534**	37.24
Population at O (1)	0.161**	4.33	0.719**	39.26
Frac. of male in the 20s at O (1)	0.452	1.08		
Frac. of female in the 20s at O (1)	1.653**	3.41		
Frac. of male in the 30s at O (1)	–0.003	0.00		
Frac. of female in the 30s at O (1)	–0.163	–0.20		
Frac. of male in the 40s at O (1)	6.816**	7.67		
Frac. of female in the 40s at O (1)	–5.513**	–6.53		
Frac. of male in the 50s at O (1)	–7.841**	–11.67		
Frac. of female in the 50s at O (1)	7.095**	11.79		
Frac. of male over 60s at O (1)	–0.410	–0.64		
Frac. of female over 60s at O (1)	1.132*	2.18		
Forest area at O (km^2) (2)	–0.005	–0.62		
Developable area at O (km^2) (2)	0.160**	3.05		
Number of museum at O (2)	–0.091+	–1.89		
Famous hot spring dummy at O (3)	0.176**	3.19		
World heritage dummy at O (4)	–0.099+	–1.65		
National park dummy at O (4)	0.112*	2.34		
Natural pres. area dummy at O (4)	0.172**	3.44		
Theme park dummy at O (4)	0.034	0.40		
Traditional area dummy at O (4)	0.161	1.30		
Traditional buid. dummy at O (4)	0.097*	2.45		
Hokkaido dummy at D			1.722**	20.14
Tohoku dummy at D			0.328**	5.29
Kanto dummy at D			0.110+	1.83
Hokuriku dummy at D			0.020	0.27
Chubu dummy at D			–0.170**	–2.78
Kinki dummy at D			–0.225**	–3.53
Shikoku dummy at D			0.027	0.40
Kyusyu dummy at D			0.871**	13.35
Forest area at D (km^2) (2)			–0.085**	–11.80
Developable area at D (km^2) (2)			0.156**	3.43
Number of museum at D (2)			0.606**	14.57
Famous hot spring dummy at D (3)			0.395**	8.43
World heritage dummy at D (4)			0.155**	2.80
National park dummy at D (4)			0.362**	9.14
Natural pres. area dummy at D (4)			0.129**	3.11
"Disney land" dummy at D (4)			2.068**	9.96
Theme park dummy at D (4)			0.165*	2.40
Traditional area dummy at D (4)			0.596**	6.13
Traditional buid. dummy at D (4)			0.202**	5.91
"Hakkeijima" dummy at D (4)			1.022**	5.52
Seaside dummy at D			0.247**	7.81

(continued)

Table 5.4 (continued)

	Trip generation model		Gravity model	
Explanatory variables	Estimate	*t*-value	Estimate	*t*-value
Difference in temp. |O-D| (2)			0.094**	10.93
Difference in long. |O-D|			−0.228**	−13.71
Constant	2.945	0.73	−8.477**	−17.96
Sigma in selection	1.897**	18.64		
Sigma in gravity			3.076**	40.77
Covariance			0.058*	2.18
Positive observation	12,514			
Number of sample	36,346			
Fraction of positive sample	0.344			
Correlation coefficient	0.604		0.674	

The marks with explanatory variable ((1) to (4)) correspond to the categories in Table 5.1
Significant level +: 10 %, *: 5 %, **: 1 %

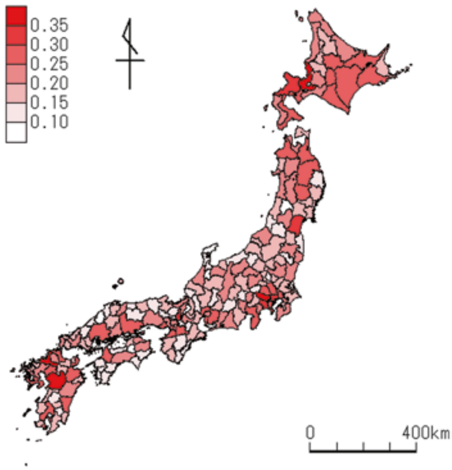

Fig. 5.6 Expected probabilities in tourism trip generation of each trip maker

destination dummies are positive and significant in Hokkaido, Tohoku, Kanto and Kyusyu but negative and significant in Chubu and Kinki. All the regional tourism resource parameters are positive and significant. Based on the t-value, the most significant factor in determining tourism demand is the number of museums, followed by "Disneyland," "national park," "seaside," "famous hot spring," "traditional area," "traditional building," "Hakkeijima," "world heritage," "theme park" and "nature reserve," in descending order. The above order suggests that tourism to urbanized areas predominates in Japan. Interestingly, the absolute difference in temperature is positive and significant, while the absolute difference in longitude is negative and significant.

It is observed that the larger absolute difference in temperature from the origin increases the number of interregional trips between seaside and mountainous areas, and between southern and northern areas. On the other hand, absolute difference in longitude tends to reduce the number of tourism trips. In other words, the majority of tourism demand can be observed between northern and southern areas, rather than between eastern and western areas. Because tourism is an activity from which people want to experience some pleasure that cannot be satisfactorily experienced in their daily lives (Zhang 2010), these findings suggest that tourists prefer to enjoy their nonroutine experience at destinations where the climate and geographical environment are different from those of their home regions. Accordingly, destination marketing should pay more attention to climate and geographical differences. For example, to increase the tourism demand in the Hokkaido region, marketing may be more effective in the Kyusyu region than in the Tohoku region. In this sense, northern and southern areas should collaborate to promote tourism demand.

The estimated parameter of area population in the trip generation model is positive, as expected. The parameter of forest area at the point of origin in the trip generation model and that of destination in the trip distribution model are both significant and negative, while those of the developable area in both models are significant and positive. Because forest area can be interpreted as an index of "nonurbanization," the trip generation model suggests that those who live in nonurbanized areas would be inappropriate as targets of tourism policies. The negative sign in the trip distribution model directly suggests that such areas are not preferred by many people as destinations for visits. However, it may be desirable from the viewpoint of local environment preservation. Therefore, careful management is required in policies concerning nature tourism. The estimated parameter of developable area is positive in both trip generation and trip distribution models. Developable area can be interpreted as "suburban area." The positive sign of the trip generation model suggests that those who live in suburban areas can be the target of tourism policy. Suppose that most suburban areas tend to be occupied by working and retired people, who are a potential segment of the tourism market. The positive sign in the trip distribution model suggests that people tend to choose tourist destinations with more suburban areas. In terms of tourism policy making, we should pay more attention to suburban areas, which often suffer from inconvenient public transportation. If some overlooked tourism resources in suburban areas were "rediscovered," they could become novel tourist destinations. The above discussion of developable areas indicates that promising interregional tourism markets are not only in areas with larger populations but also at the fringes of cities.

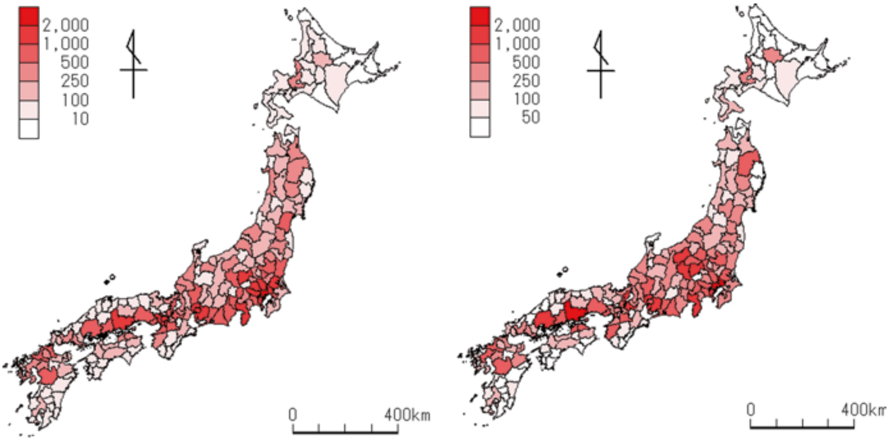

Fig. 5.7 Increase of passengers in case 1; expressway fare discount (*left*: aggregated by the origin, *right*: aggregated by the destination, trips/day)

5.5 A Simulation Analysis: Discounting Tolls of Expressways and Superexpress Railway

We established two scenarios to simulate the effects of improvement in levels of service. The simulated cases are: (1) discounting fares on all expressways by 30 % (Case 1), and (2) introducing a superexpress railway with a magnetic levitation (MAGLEV) train between Tokyo and Osaka, which reduces travel time by approximately 40 % (total travel time: 1.5 h) (Case 2), compared with the existing *Shinkansen* high-speed train. Figure 5.7 shows the simulation results of Case 1 and aggregates tourism demand at the point of origin and destination separately. Because the expressway network in Japan has already been expanded into local regions, the number of passengers from the points of origins has increased in almost all regions. The increase of trip generation as well as trip attraction is almost proportional to the population of each area. In Case 1, we find a 5 to 15 % increase of tourism passengers on holidays. Therefore, we can conclude that a fare discount policy would be very effective in stimulating interregional passenger tourism demand. Figure 5.8 shows the simulation results for Case 2. The spatial characteristics of trip generation/attraction distribution are very similar to those of Case 1, but the increase in tourism demand in Case 2 is lower than in Case 1.

The increase in tourism demand in Case 2 is seen for almost all areas when a MAGLEV service is only introduced between Tokyo and Osaka. This result stems from the composite use of MAGLEV with other transportation modes. As shown in this simulation, it is important to integrate tourism policies over various interregional transportation modes to stimulate the potential tourism market.

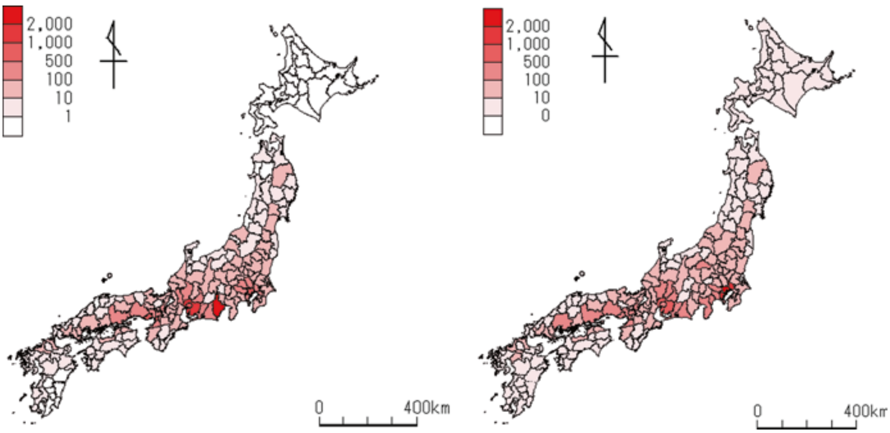

Fig. 5.8 Increase of passengers in case 2; super express railway between Tokyo and Osaka (*left*: aggregated by the origin, *right*: aggregated by the destination, trips/day)

Note that although Case 1 seems to be more effective than Case 2 in increasing tourism demand, we should note the difference between the two policies. Case 1 shows the policy of discounting expressway fares, which could increase tourism demand without any change in tourism schedules. Of course, such an increase would be welcomed by tourism industry representatives in each destination, but it would be more desirable to encourage tourists to stay for several days, because expenditure on such trips exceeds that on day trips. Case 2 refers to the policy of expanding the sojourn time for all destinations, which would influence the tourism trip schedule. The trip schedule choice model in Table 5.3 indicates that increases in sojourn time at the destination would increase the "share" of day trips in total tourism demand. At the same time, total tourism demand in our models would also increase with the expansion of sojourn time in each destination, as shown in Fig. 5.8.

The above results suggest some critical points for tourism industries considering how to attract the tourists for longer stays at each destination. We should point out that the temporal expansion of sojourn time for all destinations caused by, for example, the introduction of MAGLEV (i.e., Case 2) also means the spatial expansion of RTAs. Hence, it would cause severe competition for tourists among trip destinations. How can regional tourism policy makers address this issue? Our analyses suggest the importance of regional collaboration between types of tourism resources in neighboring areas, as indicated in the tourism schedule choice model, and the utilization of tourism resources in suburban areas, as indicated in the trip generation and distribution models. Such collaboration would further activate the interregional tourism market.

5.6 Conclusion and Future Perspectives

Regional tourism policy making requires an appropriate understanding of tourism demand characteristics. Most existing studies have focused on individual tourist behavior in a limited number of destinations. However, one overlooked issue in tourism demand analysis is the possibility of collaboration regarding tourism resources in neighboring destinations based on empirical analysis of many destinations.

This study investigates the possibility of spatial collaboration among owners of tourism resources and explains the effects of expanding sojourn time at popular tourist destinations. To investigate this possibility, we estimated a modal choice model, a trip duration choice model, and a simultaneous trip generation and distribution model. Our approach focuses on the level of service of each mode in the modal choice model. Moreover, the trip duration choice model includes sojourn time at destinations that may be reached in an RTA in 1 day, and the simultaneous trip generation and distribution model estimates the attractiveness of regional tourism resources with neighboring tourist areas. Our model system enables simulation of the effect of improvements in interregional transportation on the tourism demand, by considering the characteristics of areas in areas neighboring destinations.

From the tourism duration choice model, MST has a significant and nonlinear influence on the utility of trips of 1 day or less. Therefore, the potential market for tourism trips with accommodation lies in OD combinations with 4–6 h MST. In terms of gender and generations, females and people over 60 tend to prefer longer trips than other demographic groups, which corresponds to frequently cited target markets for the tourism industry. The estimated parameters in the tourism generation/distribution model showed that females except those in their 40s contribute most to trip generation. If other conditions are identical, trip generation from rural areas tends to exceed that from urban areas. In terms of trip distribution, tours to urbanized areas, Disneyland, traditional tourist areas or hot springs seem to be most popular in Japan. The result of absolute difference in temperature between origin and destination suggests that the potential market for tourism lies in combinations of seaside and mountainous areas, or between southern and northern areas. In short, demand for the OD combinations that provide novel experiences for tourists is expected to increase.

From the viewpoint of local government, integration in the following two aspects is important. The first is to integrate the various tourism resources. For example, collaboration with famous hot spots, national parks, and/or nature reserves will effectively prolong tourists' trip schedules. For this purpose, collaboration among tourist destinations would be effective. Concerning the maintenance of regional tourism resources, it is found that tourists expect novel experiences at destinations with different climates. Therefore, the policy of maintaining the feeling of novelty for tourists from further afield is important. In other words, regions with tourism resources should focus not only on neighboring areas to attract tourists in a conventional manner but also on distant areas to provide different tourist experiences. The simulation analysis indicates the importance of integrating tourism policy over interregional transportation modes to stimulate the potential tourism market. Policy makers should understand that the temporal expansion of sojourn time at all destinations also entails spatial expansion of the RTA. Hence, attracting tourists would cause severe competition among trip destination areas. Policies should be formulated from the perspective of collaboration between different types of tourism resources in neighboring areas and the utilization of tourism resources in suburban areas. When such collaborations occur, the interregional tourism market will be more active.

Some parts of our analysis need further improvement. Trip destination choice was not modeled directly because there is less variation in choice of destination and detailed information about levels of service. Moreover, the tourism schedule survey with multiple destinations should be analyzed more carefully considering the competition between tourism destinations. Regarding policy issues, our analysis cannot distinguish domestic from inbound trip generation because of limited data availability. Because inbound tourism policies are becoming increasingly important in Japan, as evidenced by the establishment of the JTA in 2008, it is worth comparing domestic and inbound tourism demand in the next step.

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Chapter 6
Paratransit-Adaptive Transportation Policies for Transition to Sustainability in Developing Countries

Junyi Zhang, Gang Li, S.B. Nugroho, and Akimasa Fujiwara

Abstract Paratransit in developing countries is currently an essential travel mode that provides jobs for low-income earners, but current paratransit systems are neither socially nor environmentally sustainable. This study emphasizes the importance of paratransit-adaptive transportation policies for transition to sustainability. The case studies reveal unique policy directions for the redesign of paratransit systems in developing countries according to travelers' behavior, drivers' job choice, and quality of life. It is concluded that simply eliminating paratransit services from transportation systems in developing countries may resolve the environmental issues that they cause but will surely result in more serious social issues, such as unemployment among paratransit drivers and mobility difficulties for the transportation poor. In particular, it is argued that international agencies and other donors should assist endogenous development among recipients based not only on easily applied but old-fashioned and less scientific methods but also especially on modern scientific methods adapted to local contexts.

Keywords Capability • Employment • Paratransit • Quality of life • Transport policy

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6.1 Controversies Over Paratransit in Developing Countries

In the developing world, the slow pace of public transportation systems' improvement for reasons such as a lack of sufficient financial sources caused by poor economic development, the "pro-car" attitude of governmental sectors, and difficulties in gaining public acceptance of "anti-car" policies has forced urban residents unable to afford private transport to rely increasingly on paratransit. According to Cervero and Golub (2007), over half of all public transport trips are served by paratransit.

The concept of paratransit is quite different between developed and developing countries. In developed countries, paratransit usually refers to demand-responsive and door-to-door transport services exclusively for the elderly and disabled. In developing countries, paratransit is characterized by ill-equipped vehicles but cheaper fares, flexible routing but disorderly management, and dangerous driving but convenient access. There are various paratransit modes from pedicabs and motorcycles to van-type minibuses that are operated by individuals and small companies that adapt their routing and scheduling to individual users' desires to varying degrees. Paratransit operators take the role of "gap filler" between conventional buses and private automobiles (Shimazaki and Rahman 1996; Cervero and Golub 2007). The use of paratransit provides developing countries with several advantages, such as mobility—especially for the poor—jobs for unskilled people, feeder connections between neighborhoods and trunk routes, flexibility and sensitivity to changing markets. On the other hand, paratransit also contributes greatly to issues such as traffic congestion, accidents and environmental pollution (Cervero 2000). The aberrant stopping behavior of mixed traffic with paratransit vehicles has been cited as a major reason for disorder in traffic systems (Anwar et al. 2011; Weningtyas et al. 2012a), creating pressure to eliminate rather than to try to improve it (Joewono and Kubota 2005). Despite paratransit's important role in the urban public sector of developing countries, paratransit drivers' economic sustainability is at stake. Current paratransit systems in developing cities are neither socially nor environmentally sustainable (Weningtyas et al. 2012b).

Because of the above features of paratransit in developing countries, opinions on such services are sharply polarized. Guillen and Ishida (2004) showed that inadequacy of either national or local policies has resulted in various auto-tricycle types of paratransit becoming prevalent. Diaz and Cal (2005) evaluated the impact of government regulation on the sustainability of FX (the Toyota Tamaraw FX Asian utility vehicles) types of paratransit based on a financial analysis and found a rational allocation of the service in the Philippines. Walters (2008) conducted an overview of public transport policy developments in South Africa, especially paratransit (minibus taxi) industry recapitalization programs. Her study emphasized the challenge of integrating various modes to create seamless public transport services. Schalekamp et al. (2009) evaluated three international cases of increasing paratransit regulation or incorporating paratransit into official operations and drew conclusions on the scale, timeframe and operational and institutional contexts of paratransit integration processes in the planning of public transport systems in Cape Town in South Africa and Dar es Salaam in Tanzania. On the other hand, there are studies that emphasize the role of enhancing service quality and user satisfaction to promote paratransit usage by reducing its negative effects (e.g., Joewono and Kubota 2007a, b; Tangphaisankun et al. 2009).

6.2 Quality of Life and Transportation

One of the most important purposes of transport policies is to improve people's quality of life (QOL) directly or indirectly, irrespective of a country's level of development. In line with this goal, improved levels of transportation services might allow travelers to enjoy their trips, and the accumulation of pleasant experiences may make people feel satisfied with their daily lives. In this sense, policy makers are required not only to satisfy people's basic mobility needs but also to find opportunities to improve travelers' QOL.

As a unique travel mode in developing countries, paratransit improves the necessary and highly valued mobility, especially for the poor (Cervero 2000). It also faces the challenge of retaining and attracting passengers, which is crucial for its future existence (Joewono and Kubota 2007a, b). Passengers' public transport choices depend on their perceptions of service quality (TRB 1999; Friman et al. 2001; Friman and Garling 2001). Service quality is a measure of actual service level relative to customer expectations, while quality service means conforming to customer expectations on a consistent basis (TRB 1999). Existing studies have confirmed that perceptions of paratransit service quality contribute to its use (Joewono and Kubota 2007a, b; Tangphaisankun et al. 2009; Tarigan et al. 2010).

QOL is defined differently in various disciplines, and there is no unified method of measuring it, but it is known that subjective elements play a major role in its measurement; in particular, life satisfaction and happiness are two of the core attributes (Phillips 2006). Life satisfaction is an overall assessment of feelings and attitudes about one's life at a particular point in time and ranges from negative to positive. It is one of three major indicators of subjective well-being: life satisfaction, positive affect, and negative affect (Diener and Lucas 1999). The literature reveals that life can be construed as a general combination of many specific domains. Life satisfaction can be understood as the result of satisfaction in the domains of life, such as health, economy, job, family, friendship, and personal and community environment (Rojas 2006). One important domain is work. Life satisfaction is identified as significantly related to job satisfaction (Ghiselli et al. 2001). Feelings about work are transferred to general life in affective spillover processes, while individuals review their current work and life utilities rationally in cognitive appraisal (Song et al. 2008). The need for happiness is deeply felt by humans and reflects the level of positive or negative affect perceived from daily experiences. Life satisfaction and happiness constitute a significant part of subjective QOL (Ventegodt et al. 2003). One study only infers that comfort-related characteristics are placed second in service quality priorities regarding negative experiences, which indirectly indicates QOL as the second consideration in service quality of paratransit (Joewono and Kubota 2007a, b).

6.3 Objectives of This Study

Given the salient features of paratransit, it is urgent that appropriate decisions be made regarding its position within the transportation systems of developing cities; that is, paratransit either should be limited or even eliminated because of its negative impact or should be used more effectively because of its positive impact. Therefore, this research intends to undertake a comprehensive analysis of both demand and supply of paratransit systems in developing cities. The analysis has the following objectives.

1. To evaluate the effects of availability of paratransit as a major access/egress mode, and to identify captive travel modes for paratransit users.
2. To clarify the cause–effect relationships of paratransit users' perceptions on service quality, happiness during travel and satisfaction with life.
3. To analyze paratransit drivers' job choice behavior under various policy interventions, and to identify the influential factors and whether there are "captive jobs" for paratransit drivers.
4. To clarify the cause–effect relationships regarding paratransit drivers' jobs, reasons for drivers' job choices, their businesses and their QOL.

6.4 Travel Mode Choice Analysis for Redesign of Paratransit Systems in Developing Countries

To mitigate the negative aspects of paratransit in developing countries and to make effective use of its advantages, the current transportation systems require thorough redesign, not complete elimination. To meet this challenge, a better understanding of its passengers' travel mode choice behavior is important. To date, various policies and plans have been proposed by international agencies and local governments. Supply-oriented philosophy has dominated debates, and users' choices have unfortunately been neglected. To resolve the current traffic issues in developing countries, policies to increase transportation supply are crucial; however, the benefits will be limited without sufficient measures to target travel demand. Therefore, this part of the study will investigate how paratransit users in developing countries would behave under different policy scenarios reflecting a variety of travel modes and the decision-making mechanisms specific to paratransit users. The Jabodetabek Metropolitan Area (JMA) in Indonesia was selected because of the popularity of various types of paratransit. A stated preference (SP) approach was adopted to incorporate the influence of various possible policies in a logical manner.

6.4.1 Features and Issues of Paratransit in Jabodetabek Metropolitan Area

The main paratransit modes in the JMA are *becak*, *ojek*, *bajaj*, and *angkot*, which constitute a hierarchy of services complementary to the inadequate official public

Fig. 6.1 Typical paratransit vehicles in Jabodetabek metropolitan area, Indonesia

transportation system (see Fig. 6.1). A *becak* is a three-wheeled pedaled bicycle taxi offering door-to-door neighborhood services for a negotiable fare. They are banned in DKI Jakarta but not in other places in the JMA (Cervero 2000). An *ojek* is a motorcycle taxi hired for a negotiated fare. It also provides door-to-door connectivity but with the advantages of greater speed and travel range compared with a *becak*. It is actually a private vehicle but for public use, so it is an entirely illegal public transport mode. A *bajaj* is a sort of registered auto-rickshaw taxi with three wheels that also offers a door-to-door service for a negotiated fare. Additionally, it is allowed to cross major roads but cannot travel on them in DKI Jakarta. An *angkot* is a popular public mode with a fixed route but without a fixed schedule. It follows a designated route in the city's network. Additionally, various types of cars and vans with a capacity of 12–16 seats are used as *angkot* (Joewono and Kubota 2007b).

6.4.2 Stated Preference Survey

Because of the constraints of income and insufficient transportation supply in developing cities, the availability of travel modes may affect people's daily mobility significantly, and many travelers may be captive to specific travel modes. However, this has not been thoroughly examined in the context of developing countries. To fill this gap, this study conducted an SP survey (Kroes and Sheldon 1988; Polak and Jones 1997; Hensher 1994) in the JMA with respect to the above four types of paratransit and five official travel modes; i.e., train, mass rapid transit (MRT), bus, bus rapid transit (BRT), and car.

Attributes included in the SP survey of this study were specified based on the current situation, opinions of local experts, and a literature review. As a result, 14 attributes were included: nine attributes concerning the availability of travel modes (five for access modes, two for egress modes, and two for major travel modes together with their travel time), three attributes of travel time for the major travel modes: train, BRT, and bus, and the other two attributes of trip purpose and trip distance, respectively. MRT was also introduced as a main travel mode but with travel time fixed with respect to trip distance. Each of the above attributes had two or three levels. The cost of each travel mode was fixed according to trip distance, and walking is considered to be available as both an access and egress mode. Based on an orthogonal fractional factorial design, 27 SP profiles were obtained. To reduce the burden on respondents, the 27 SP profiles were further randomly grouped into nine balanced blocks, and each respondent was only asked to answer one block with three SP questions, each of which included 4–6 main travel mode options. The main modes were train, MRT, bus, BRT, *angkot* and car.

The questionnaire including the above SP questions consisted of five parts. The first part began with questions about paratransit use and the corresponding evaluations of service quality. The second part investigated household vehicle ownership and usage. In the third part, respondents were asked to report their individual characteristics, their use of vehicles owned by households, their happiness perceived when conducting trips, and their satisfaction with life (life satisfaction). A 1-day trip diary was recorded for the fourth part. Finally SP questions about travel mode choice were included. Before the SP question, there is a brief introduction to MRT, which does not currently exist. Note that the data collected are also used in the analysis in Sect. 6.5.

A home interview survey was conducted from February to March 2010 for people living in the JMA who had used any type of paratransit, and the questionnaires from 702 respondents and 2,106 SP profiles (702 respondents * 3 SP profiles per respondent) were collected. When invalid samples were excluded, 1,902 samples were used for this study. In the sample, the proportions of males and females were almost the same: 33.8 % of respondents were company officers, 31.3 % were students, 15.7 % were government officers, and 7.4 % were self-employed. The household income of 23.4 % of respondents was less than 2.0 million Rp (Indonesia rupiah), 36.9 % between 2.0 and 4.0 million Rp, 21.0 % between 4.0 and 6.0 million Rp, and 18.7 % higher than 6.0 million Rp.

When it was conducted, this was the first comprehensive SP survey in the literature to examine the use of paratransit in developing cities.

6.4.3 Capturing Factors of Travel Mode Choice Behavior

To represent people's travel mode choice behavior clearly, a dogit model (Gaudry and Dagenais 1979) is adopted. Its general form can be expressed as follows:

$$P_{ni} = \frac{e^{V_{ni}} + \theta_i \sum_j e^{V_{nj}}}{(1+\sum_j \theta_j)\sum_j e^{V_{nj}}}, i, j = 1, 2, \ldots, I \qquad (6.1)$$

where n and i (or j) indicate traveler and choice alternative, respectively, P_{ni} refers to the probability that traveler n chooses travel mode i from I travel modes, V_{ni} is the deterministic term of the utility function of travel mode i, and θ_i means the (nonnegative) captivity parameter specific to a travel mode i (the larger the value of θ_i, the greater captivity to travel mode i). Alternative-specific attributes, availability of travel modes for access/egress and as main modes as well as individual attributes are included in V_{ni}.

The model estimation results are shown in Table 6.1. Model accuracy, indicated by McFadden's rho-squared, is 0.092. This is not sufficiently high to predict behavior

Table 6.1 Estimation results of Dogit model for travel mode usage behavior

Parameter		Train	MRT	Bus	BRT	*Angkot*	Car
Constant term			−1.92	2.53	−4.63		
Level of service	Travel time	−1.02**					
	Travel cost	−1.57**					
Individual attributes							
Male (yes: 1, no: 0)			−8.86*	−1.42	0.12	−1.08	−2.23
Government officer (yes: 1, no: 0)			15.6**	7.76 *	−3.08	−20.83	5.86 **
Student (yes: 1, no: 0)			2.75	5.01	2.38	1.35	9.33**
Household monthly income less than 2 million Rp (yes: 1, no: 0)			1.29	6*	2.92	9.8	−15.79
Availability of travel mode							
Becak as ACCESS modes to (yes: 1, no: 0)			−2.92	2.45	−1.34	−13.48**	
Ojek/bajaj as ACCESS modes to (yes: 1, no: 0)			−20.7	−1.14	−2.38	−11.94	
Angkot as ACCESS modes to (yes: 1, no: 0)			5.92	6.85*	1.58	−1.98	
Ojek as EGRESS modes to (yes: 1, no: 0)			3.18	−6.46*	−2.8	6.83	
Bajaj as EGRESS modes to (yes: 1, no: 0)			−9.93**	−4.36	0.69	−2.64	
Of *angkot* as MAIN modes to (yes: 1, no: 0)			−0.22	−7.71**	2.44		
Car as MAIN modes to (yes: 1, no: 0)			−6.11*	2.13	0.05	−4.36	
Captivity parameters		1	0.4***	0.75***	0.71***	0.92***	0.32***
Initial log likelihood		−3163.79					
Converged log likelihood		−2871.24					
McFadden's Rho-Square at zero		0.092					
Sample		1,902					

*, **, *** represent 90 %, 95 % and 99 % significance levels, respectively

but is acceptable for examining the influence of the availability of paratransit and cars on travel mode usage behavior and for identifying captive travel modes.

Availability of paratransit modes is classified according to two modes: access/egress mode and main mode. From Table 6.1, it is found that small paratransit vehicles—*becak*, *ojek* and *bajaj*—either have no effect on the use of some main modes, indicated by insignificant parameters, or have a negative influence on main mode usage. *Becak* as an access mode has a significantly negative effect on the use of *angkot* as a main mode, and *ojek* and *bajaj* as egress modes also have obvious negative impacts on the main modes of bus and MRT, respectively. Such negative influences reduce the utility of the corresponding main modes. It may be inferred that paratransit users do not need to take access/egress modes to or from the main mode and/or to reduce transport fees by avoiding transfer by paratransit compared with walking. It is confirmed that using large paratransit vehicles (i.e., *angkot*) as an access mode promotes the use of buses as a main mode. This accords with the current situation in the JMA (*angkot* and bus combinations are quite common). The effects of availability of the main modes of *angkot* and car reveal that *angkot* and buses would still compete fiercely, just as they do currently. The estimation result regarding the availability of cars suggests that the introduction of an MRT would effectively reduce car use. This may be because an MRT can provide a very high level of service compared with other public modes.

With regard to captivity, it is surprising that paratransit users are captive with different probabilities to all travel modes, indicated by all statistically significant captivity parameters. Among all modes, travelers are most captive to trains. SP survey results show that the chosen shares for trains, MRT, buses, BRT, *angkot* and cars are 30 %, 10 %, 18 %, 21 %, 14 % and 6 %, respectively, where train travel enjoys the largest share. The highest share for trains may be because fares are lowest and the travel time moderate among the six main modes in the hypothetical choice scenarios. *Angkot* is the second main mode in terms of captive use when they are available. Perhaps this is attributable to having the shortest travel time over short distances and the third cheapest fare. Buses and MRT follow *angkot* in sequence. Although buses take third place, indicated by the third largest parameter, the difference in terms of captivity could be neglected, as revealed by parameters of 0.75 and 0.71. It is natural that MRT is the least captive form of travel among the public modes because it is the most expensive mode, and people are not familiar with it. Cars are last on the list because of the huge financial investment, especially for the poor. The order of magnitude of captive parameters generally coincides with the order of fares, which indicates that fare will remain a very important influence on mode choice behavior in future.

As for the main indicators of service quality, travel time and travel cost are statistically significant at the 95 % level (all the parameters are logically negative), indicating that such service factors are always important in travel mode decisions. In terms of paratransit users' individual attributes, females have a strongly negative attitude toward MRT. Government officers tend to choose car, MRT and bus, probably because their living standards are generally better than those of other people in developing countries, and they can therefore afford a private mode (car) and more expensive improved transit systems such as MRT and buses (MRT and buses are the first and second most expensive main public modes in the SP design, respectively). Surprisingly, students also prefer cars, suggesting that they have high expectations for the future. Although buses and *angkot* currently compete fiercely, the model results reveal that people with the lowest income will clearly prefer buses in future.

6.4.4 Policy Implications

Dogit model estimation results reveal that *bajaj*, *ojek* and *becak* as access and/or egress modes have no impact or a significant negative impact on the use of main modes. This implies that the use of small paratransit vehicles as access/egress modes does not promote public transport for current paratransit users. If this conclusion remained true in analyses of large-scale survey data, it would mean that reorganizing small paratransit networks as feeders of official public transport networks should not be included in policy menus to realize transitional sustainability. However, as the latter part of this chapter explains, because many low-income people in developing countries drive such small paratransit vehicles, it is necessary to keep such vehicles for a certain time to supply job opportunities to low-income people and to secure social stability. It seems better to position such vehicles as main modes at the community and neighborhood levels (i.e., for short-distance trips) rather than as access/egress modes. Generally, communities and neighborhoods are much larger in developing megacities like the JMA. This argument may also be supported by the fact that budget limitations in developing countries make it almost impossible to service urban transportation networks mainly with MRT and BRT, which are environmentally friendly and efficient.

Because the combination of *angkot* and buses is preferred in the present and this will remain true in future, policies to improve *angkot* service quality (e.g., introducing new types of vehicles and improving networks) should be promoted.

Although statistically insignificant, the constant term of BRT is negative and much larger than other mode-specific constant terms, indicating that unobserved factors tend to keep paratransit users away from BRT. This may reflect unsatisfactory service aspects of BRT transport. This observation also applies to MRT but not to buses, for which the constant term is positive. Considering the above findings, policy makers in the JMA should pay careful attention to the negative aspects of BRT and MRT in the daily operation and future expansion of their networks.

6.5 Paratransit Service Quality and Users' Quality of Life

Paratransit in developing countries satisfies a large number of people's various mobility needs. It is true that paratransit services supported by ill-equipped vehicles, low-skilled drivers, and disorderly management in a mixed traffic environment cannot meet adequate service standards in developed countries. It is known that people's lives and behavior depend on context. It is therefore reasonable that people in developing countries expect less from transport services than those in developed countries. Because it is unlikely that they have *no* expectations, people in developing countries also patronize paratransit services based on evaluations of their own satisfaction, but paratransit has become an indispensable part of transportation systems, so people rely heavily on it in their daily lives. Therefore, people's accumulated experience of paratransit may have a significant influence on their QOL.

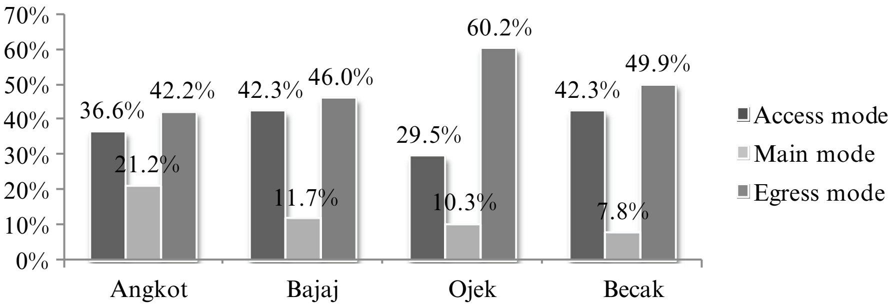


Fig. 6.2 The role of paratransit in people's daily mobility

Unfortunately, little research has been conducted with respect to the relationship between transport services and QOL, especially in developing countries. Motivated by this research gap, this section investigates the cause–effect relationships among paratransit users' perceptions of service quality, happiness during travel, and life satisfaction (a typical QOL indicator).

6.5.1 Data

In this section, the questionnaire survey data collected in the previous section are used, and four typical types of paratransit—*angkot*, *bajaj*, *ojek*, and *becak*—are targeted. Related to this part of the study, the questionnaire items include: (1) individual characteristics such as age, gender, job, and household monthly income; (2) respondents' perceptions of paratransit service performance (i.e., service quality); (3) paratransit use for daily trips (frequency and use of paratransit to access other modes, main modes of travel and the egress from other modes); (4) happiness when traveling for different purposes; and (5) life satisfaction in various domains. For items (2), (4), and (5), respondents were asked for their subjective responses on five-point scales (service quality and life satisfaction: "1: very dissatisfied … 5: very satisfied"; happiness during travel: "1: very unhappy … 5: very happy").

Our survey results show that most respondents use *bajaj*, *ojek* and *becak* very infrequently, but 34.0 % of respondents use *angkot* almost every day. Figure 6.2 reveals that respondents use several types of paratransit for various functions simultaneously. The use of *bajaj* and *becak* for both access and egress are similar. In contrast, they are reluctant to use *bajaj*, *ojek* and *becak* as main modes of travel. *Ojek* is used mainly for egress from other modes (61.3 %). *Angkot* is preferred as a main mode (21.2 %).

Users' perceptions on service quality of paratransit are shown in Table 6.2, where the two highest scores are in bold and the two lowest scores are in italics for each type, respectively. Users are most satisfied with the operational frequency and fares for *angkot,* but they do not like the drivers' manner and are concerned about air

Table 6.2 Satisfaction level of paratransit services

	Angkot		Bajaj		Ojek		Becak	
Service aspects	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Fare	**3.11**	0.82	2.67	0.65	2.79	0.78	2.95	0.75
Travel time	2.77	0.87	2.71	0.77	**3.69**	0.77	*2.55*	0.79
Punctuality	2.61	0.87	2.69	0.78	**3.65**	0.81	*2.51*	0.83
Convenience	2.73	0.88	2.29	0.76	3.01	0.71	3.10	0.82
Comfort	2.76	0.78	2.59	0.73	3.14	0.77	2.96	0.74
Connectivity to other modes	3.09	0.79	**2.88**	0.77	3.28	0.80	2.86	0.78
Traffic safety	2.74	0.83	2.54	0.77	*2.70*	0.73	3.02	0.81
Security (criminal)	2.53	0.83	2.58	0.79	2.74	0.75	2.89	0.79
Operation frequency	**3.20**	0.85	2.79	0.73	3.29	0.78	2.67	0.78
Operation routes	3.03	0.83	2.78	0.77	3.38	0.81	2.70	0.74
Operation hours	3.05	0.81	**2.86**	0.73	3.35	0.82	2.72	0.74
Coverage area	3.03	0.79	2.70	0.74	3.31	0.80	2.70	0.76
Travel information	2.93	0.82	2.67	0.72	3.05	0.76	2.75	0.71
Driver manner	*2.41*	0.85	2.37	0.79	2.84	0.79	2.97	0.72
Air pollution caused	*2.45*	0.90	*1.84*	1.01	*2.72*	0.80	**3.59**	1.26
Noise caused	2.52	0.82	*1.79*	1.06	2.78	0.74	**3.56**	1.24
Sample size (persons)	453		428		457		371	

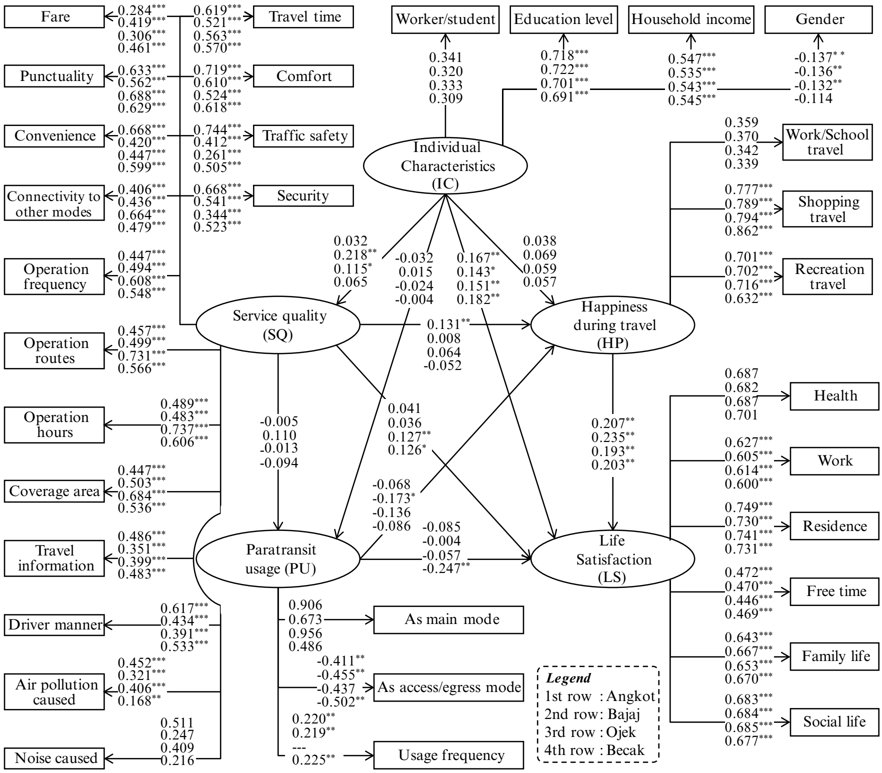
pollution. *Bajaj* users give the highest scores for the connectivity of paratransit to other travel modes and hours of operation. However, the air pollution caused by *bajaj* is perceived as unsatisfactory. It is quite reasonable for users to evaluate travel time and punctuality for *ojek* highly in terms of service. The lowest score for traffic safety indicates the users' concern about the stability of motorcycles, potential accidents and high risk of physical injury. Because a *becak* is pedaled, it naturally receives the highest scores for the service in terms of air pollution and noise; in contrast, users give it the lowest evaluation on punctuality and travel time.

6.5.2 *Observations Based on a Cause–Effect Analysis*

A structural equation model (SEM) with latent variables (Jöreskog and Sörbom 1989) is used to capture the complicated cause–effect relationships in evaluations of "service quality," "paratransit usage," "happiness during travel," "life satisfaction," and "individual characteristics," which are described as latent variables. Needless to say, paratransit provides the service of transporting passengers. It is natural to assume that "service quality" influences "paratransit use," and the better the service, the more frequently it is used (direct effects). Users experience the service when using paratransit on a daily basis, and word-of-mouth information from other passengers may engender feelings during travel. Both real-time and accumulated experience may affect "happiness during travel," where the influence of the former is called a "direct effect" (from "service quality" to "happiness during travel") and that of the latter an "indirect effect" (from "service quality" to "paratransit use" and then to "happiness during travel"). Paratransit is for participating in various daily activities, which satisfy users' needs and consequently influence their satisfaction with life. This is described as the direct effect from "paratransit usage" to "life satisfaction." "Life satisfaction" may be influenced by various environmental factors, among which the service provided by paratransit may be included. This motivates us to introduce the direct effect from "service quality" to "life satisfaction." "Life satisfaction" is usually influenced by various psychological factors, among which "happiness during travel" is included as one element. The above expected cause–effect relationships probably differ across individuals. To represent such individual heterogeneity, the direct effects of "individual characteristics" on the other four latent variables are also assumed. The estimation results of the SEM with the above cause–effect structures are shown in Fig. 6.3. The overall goodness-of-fit indices (GFI (AGFI), for *angkot*, *bajaj*, *ojek* and *becak* are 0.789 (0.755), 0.791 (0.757), 0.791 (0.756), and 0.800 (0.767), respectively) together with statistical performance and parameter signs support the assumed model structures.

Positive direct effects between the three subjective evaluation indicators of "life satisfaction," "happiness during travel" and "service quality" are observed, except for *becak*, for which the direct effect from "service quality" to "happiness during travel" is negative but statistically insignificant. The negative effect for *becak* is probably because it is a pedal tricycle, and consequently, users may feel unhappy when using it. From "service quality" to "happiness during travel," the direct effect is only confirmed for *angkot*. This may be because the other three types of paratransit can only provide the most fundamental transport service with ill-equipped vehicles and an extremely narrow riding space, which may bring little pleasure to users. This is partially supported by the lower evaluation scores for service quality for *bajaj* and *becak*. Although the scores of a majority of service quality items for *ojek* are higher than those for *angkot*, the higher satisfaction levels may be because of lower expectations, which are not high enough to make people feel happy. "Service quality" only influences "life satisfaction" for *ojek* and *becak*, and this may be because these two types are the most commonly used for routine trips. The direct effect from "paratransit usage" to "life satisfaction" is confirmed only for *becak*. This is probably because *becak* is always used for the most essential short trips. As expected, "happiness during travel" significantly influences "life satisfaction" for all four types of paratransit.

Among the standardized total effects, "happiness during trip" shows the highest influence on "life satisfaction" for *angkot*, *bajaj*, and *ojek* users, and is much greater than that of "service quality." It is also found that the improved service quality in each aspect enhances life satisfaction, and government/company officers or male students with higher education levels and household monthly incomes feel more satisfied with their lives. Among the three aspects of "happiness during travel," enhancing happiness during travel for work or school contributes most to "life satisfaction." For "service quality," cost of fare has the strongest influence on "life satisfaction" for *angkot* users, followed by connectivity to other modes, coverage areas, operational frequency, travel information, air pollution caused by paratransit, and operation routes. It is a new finding that air pollution caused by *angkot* has a higher influence on life satisfaction than many aspects of paratransit service. Similar rankings for



(*: significant at 10% level; **: at 5% level; ***: at 1% level)

(STE: Standardized total effects)

STE	Angkot				Bajaj				Ojek				Becak			
	IC	SQ	PU	HP	IC	SQ	PU	HP	IC	SQ	PU	HP	IC	SQ	PU	HP
SQ	0.032				0.218				0.115				0.065			
PU	-0.032	-0.005			0.039	0.110			-0.026	-0.013			0.002	0.094		
HP	0.044	0.132	-0.068		0.064	-0.110	-0.173		0.070	0.066	-0.136		0.054	-0.060	-0.086	
LS	0.180	0.069	-0.100	0.207	0.166	0.034	-0.036	0.235	0.181	0.140	-0.083	0.193	0.200	0.090	-0.264	0.203

Fig. 6.3 Estimation results of the structural equation model

the service aspects of *bajaj*, *ojek* and *becak,* crucially influencing "life satisfaction," are also confirmed.

"Happiness during travel" is most influenced by "paratransit usage," except for *angkot*. Using paratransit as a main mode reduces the happiness experienced during a trip as well as life satisfaction; however, using paratransit as an access/egress mode improves happiness during a trip and the resulting life satisfaction. Furthermore, using paratransit more frequently reduces the feeling of happiness during travel. "Happiness during travel" is unfortunately not influenced by "individual characteristics." The observation about the influence of "service quality" on "life satisfaction" is also applicable to "happiness during travel" for *angkot*.

"Service quality" is only influenced by "individual characteristics" for *bajaj* and *ojek*. For these two services, gender shows the highest influence on service quality, followed by identification as a worker/student. Females, workers and students evaluate service quality higher than males and those with other types of employment status, respectively. Paratransit usage does not show any clear differences across individuals because the direct effects from "individual characteristics" to "paratransit usage" are insignificant for all four types of paratransit.

6.5.3 Policy Implications

Because of the disorderly management of paratransit systems and the resulting troublesome issues, experience in developed countries may suggest that it is better to remove the paratransit services from official transportation systems in developing countries at some point. Unfortunately, it is almost impossible to remove paratransit considering its popularity, insufficient official transportation services, and employment opportunities for low-income earners. To achieve the eventual goal of sustainable urban and transportation development in developing countries, the transitional process cannot be ignored. A "frog leap" also needs public acceptance. Paratransit will still continue to play an important and indispensable role in transportation systems in developing countries until the sufficient official public transportation services are provided and the employment issues of the "paratransit industry" are resolved. Therefore, policy makers are required to focus on the issues in the transitional process to sustainable development.

This case study confirms that QOL matters in paratransit transportation issues, as does service quality. Although happiness during travel is only influenced by service quality for *angkot* and *bajaj*, it influences the life satisfaction for all four paratransit types. This confirms that for all paratransit types, service quality has indirect effects on the life satisfaction of passengers. This means that improved transport services may improve people's QOL. Service standards adapted to the contexts of developing countries should be established, and the corresponding evaluation and monitoring procedure should be introduced. Because paratransit as a main travel mode does not positively influence life satisfaction, paratransit systems should be reorganized to support official transportation systems. During the transitional process, the environmental performance of paratransit vehicles should be improved. In addition to the most fundamental aspect of fares, the importance of travel information provision should be emphasized. This can be well supported by the rapid progress of information and communication technologies in developing countries, especially among the younger generation.

6.6 Paratransit Drivers' Job Performance and Life Satisfaction

Paratransit drivers, as a low-income group in developing societies, play a significant role in offering vital daily transport services in developing cities. During the transitional period of sustainable development in developing countries, policy

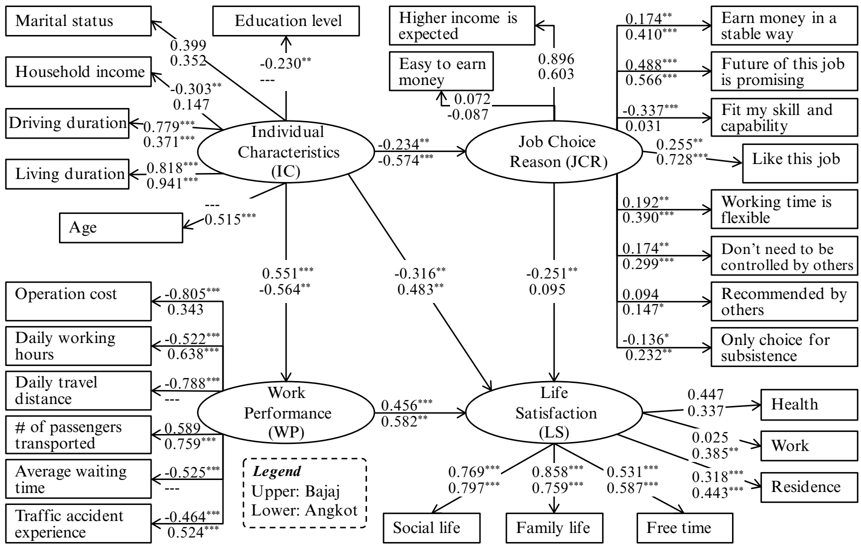
Table 6.3 Profiles of paratransit drivers participated in the survey

Individual characteristics		Bajaj drivers # of samples	%	Angkot drivers # of samples	%
Gender	Male	194	100.0	205	100.0
Age	<30 years old	39	20.1	21	10.2
	30–39 years old	67	34.5	99	48.3
	40–49 years old	52	26.8	70	34.1
	≥50 years old	36	18.6	15	7.4
Marital status	Single	24	12.4	14	6.8
	Married	170	87.6	191	93.2
Education level	Elementary school or below	60	30.9	15	7.3
	Secondary school	93	47.9	78	38.0
	High school or above	41	21.2	112	54.7
Household monthly income	<1.0 Indonesian rupiah (Rp)	43	22.2	30	14.6
	1.0–2.0 Indonesian rupiah (Rp)	117	60.3	95	46.3
	>2.0 Indonesian rupiah (Rp)	31	16.0	79	38.5
	Missing	3	1.5	1	0.6
# of paratransit drivers surveyed		194		205	

makers should pay more attention to paratransit drivers' lives for the smooth operation of transportation systems. However, research related to paratransit drivers' job conditions and their operations is quite rare. To fill this gap, this study aims to clarify the relationships between paratransit drivers' job performance and life satisfaction to provide useful insights into the policy decisions about transitional sustainability.

6.6.1 Stated Job Choice Survey

A questionnaire survey was conducted by face-to-face interviews in the JMA from February to March 2010. The targeted respondents were drivers of four typical forms of paratransit: *angkot*, *bajaj ojek* and *becak*. The questionnaire consisted of seven parts. The first part began with the requirement to complete the drivers' 1-day diary of transporting passengers. The second part investigated the profiles of their passengers. Questions about the basic information of the paratransit vehicles in current use were included in the third part. The fourth part contained questions about the current job conditions and reasons for choosing this job. The fifth part consisted of a series SP questions about future job choices under various policy interventions (for details, refer to Sect. 6.7). The final two parts collected paratransit drivers' individual information and their family information, respectively. The total number of valid responses was 799. The individual characteristics of each type of paratransit driver are summarized in Table 6.3. Below, only *bajaj* and *angkot* drivers will be discussed.



(*:significant at 10% level;**: significant at 5%level; ***: significant at 1% level)

Standardized total effects	Bajaj				Angkot			
	IC	JCR	WP	LS	IC	JCR	WP	LS
JCR	-0.234				-0.574			
WP	0.551				-0.564			
LS	-0.005	-0.251	0.456		0.100	0.095	0.582	
Satisfaction with social life	-0.004	-0.193	0.351	0.769	0.080	0.076	0.464	0.797
Satisfaction with family life	-0.004	-0.216	0.392	0.858	0.076	0.072	0.442	0.759
Satisfaction with free time	-0.003	-0.134	0.242	0.531	0.059	0.056	0.342	0.587
Satisfaction with residence	-0.002	-0.080	0.145	0.318	0.044	0.042	0.258	0.443
Satisfaction with work	0.000	-0.006	0.011	0.025	0.039	0.037	0.224	0.385
Satisfaction with health	-0.002	-0.112	0.204	0.447	0.034	0.032	0.196	0.337

Fig. 6.4 Estimation results of structural equation model with latent variables

6.6.2 Hypotheses

In this section, paratransit drivers' life satisfaction is analyzed by investigating its relationships with reason for job choice, work performance and drivers' individual characteristics. The hypotheses of this analysis are: (1) paratransit work performance has a positive influence on life satisfaction, (2) job choice reason has a significant influence on life satisfaction, which differs across types of paratransit drivers, and (3) job choice reason, work performance and life satisfaction are heterogeneous across drivers. To capture the above complex cause–effect relationship, a SEM is used with latent variables representing "job choice reason," "work performance," "life satisfaction" and "individual characteristics." Observed variables related to each latent variable and the overall model estimation results (both direct and total effects) are shown in Fig. 6.4.

6.6.3 Findings and Policy Implications

Our assumed model structure is statistically supported by acceptable goodness-of-fit indices (GFI (AGFI): 0.727 (0.676) for *bajaj* drivers and 0.707 (0.649) for *angkot* drivers), statistical significance, and expected signs of the parameters included in the model.

"Life satisfaction" is significantly affected by "work performance," "job choice reason" and "individual characteristics" for two types of paratransit drivers, but "job choice reason" has no significant effect on *angkot* drivers. Among standardized total effects, "work performance" shows the highest influence on "life satisfaction" for both *bajaj* and *angkot* drivers, and this influence is much greater than those of "individual characteristics" and "job choice reason." The most strongly influenced life domains are family life and social life, and the least influenced are work for *bajaj* drivers and health for *angkot* drivers. As for the influence of observed variables described by exogenous latent variables on life satisfaction, a smaller absolute parameter value indicates a larger influence. The most influential factor of "work performance" in "life satisfaction" is traffic accidents experienced by *bajaj* drivers and operational cost for *angkot* drivers, followed by daily working hours for both. The least influential factor is operating cost for *bajaj* drivers and number of passengers transported for *angkot* drivers. Waiting time influences *bajaj* drivers but is not relevant to *angkot* drivers. Surprisingly, number of passengers transported is not significant in the *bajaj* drivers' evaluation. Daily travel distance is not relevant to *angkot* drivers' evaluations of work performance, probably because *angkot* routes are fixed. Focusing on the most influential traffic accident experience, the *bajaj* drivers' experience negatively influences life satisfaction, but *angkot* drivers show the opposite trend. Because a *bajaj* is a three-wheel paratransit vehicle and has no fixed routes, driving one is less stable and more risky than driving an *angkot*. In contrast, because an *angkot* is a bus-type paratransit vehicle and its routes are fixed, drivers are more familiar with routes than *bajaj* drivers and consequently may become more careless during driving. It is especially important that *angkot* drivers need to collect passengers while driving. These features probably lead to more accidents caused by drivers. In this sense, for both types of drivers, policies to improve paratransit services should focus on traffic safety. To improve drivers' life satisfaction further, policies to reduce operation cost, working hours, driving distances, and waiting times for *bajaj* drivers and to collect passengers effectively for *angkot* drivers should be promoted.

Among the reasons for this job choice (note that a smaller absolute parameter value indicates a stronger influence on life satisfaction), "only choice for subsistence" (i.e., capability), "don't need to be controlled by others" (i.e., freedom), and "earn money in a stable way" (i.e., stability) are the most important factors affecting the life satisfaction of *bajaj* drivers, and "recommended by others" (i.e., job reputation and reliability), "only choice for subsistence," and "don't need to be controlled by others" are most important for *angkot* drivers' life satisfaction. The stronger influence of capability on life satisfaction suggests that regulating paratransit in developing countries may deprive drivers of the only means of earning money for subsistence.

In this sense, it is extremely important to secure their jobs by mitigating the negative aspects of paratransit to increase public acceptance of transportation policies.

Because "individual characteristics" influence all other three latent variables, the revealed cause–effect relationships differ significantly across drivers. Therefore, policy decision makers should pay careful attention to such heterogeneity. In other words, there are no "one size fits all" policies that are applicable to every driver. Policies focusing on different types of paratransit drivers are required. Accordingly, Fig. 6.4 suggests that education level and household income are more important in improving *bajaj* drivers' work performance and life satisfaction than other factors, while the most influential factor for *angkot* drivers is driving duration, followed by age. It is obvious that effective paratransit policies are different for the two segments of drivers. For *angkot* drivers, policies supporting younger drivers' jobs could effectively improve their QOL. In contrast, policies to increase household income by securing job opportunities would be more effective in improving *bajaj* drivers' QOL.

6.7 Paratransit Drivers' Job Choice and Sustainable Policies: A Case Study in Jabodetabek Metropolitan Area

In Sect. 6.6, paratransit drivers' job behavior was analyzed with a focus on work performance and life satisfaction. It was revealed that drivers' lives should be properly considered in policy decisions on the future paratransit systems in developing countries. Effective and socially acceptable paratransit policy makers need better understanding of paratransit drivers' future employment under various policy interventions for sustainable urban development. For this purpose, an SP survey was implemented in the JMA, together with the survey explained in Sect. 6.6 of *angkot*, *bajaj*, *ojek*, and *becak* drivers.

6.7.1 Profiles of Paratransit Drivers in the JMA

The profiles of four types of paratransit drivers are illustrated in Table 6.4. All paratransit drivers are male. *Becak* drivers are younger, corresponding to the obvious feature of the *becak* job that it is a physically demanding job that is not suitable for older people. The *bajaj* drivers show the opposite trend. *Ojek* drivers are a little older than *becak* drivers. The ages of *angkot* drivers are concentrated in the range from 30 to 49 years old. Generally, most *ojek* drivers are single, inferred by the highest share of single status in marital status among the four types of paratransit drivers, among whom an overall proportion of approximately 26 % are single. Single people are most likely to be *becak* drivers, probably because their education level is low and they are less skilled. In contrast, the proportions of single people are lower among *bajaj* and *angkot* drivers. The proportions of drivers with children follow the order: *angkot* drivers > *bajaj* drivers > *becak* drivers > *ojek* drivers.

Table 6.4 Profiles of four types of paratransit drivers

Driver Characteristics		*Becak* No.	*Becak* %	*Ojek* No.	*Ojek* %	*Bajaj* No.	*Bajaj* %	*Angkot* No.	*Angkot* %
Gender	Male	192	100	208	100	194	100	205	100
Age	<30 years old	67	34.9	73	35.1	39	20.1	21	10.2
	30–39 years old	76	39.6	74	35.6	67	34.5	99	48.3
	40–49 years old	43	22.4	45	21.6	52	26.8	70	34.1
	>50 years old	6	3.1	16	7.7	36	18.6	15	7.3
Marital status	Single	47	24.5	54	26.0	24	12.4	14	6.8
	Married	145	75.5	154	74.0	170	87.6	191	93.2
	Has children	138	71.9	137	65.9	160	82.5	185	90.2
Education level	Elementary school or below	98	51.0	18	8.7	60	30.9	15	7.3
	Secondary school	89	46.4	76	36.5	93	47.9	78	38.0
	High school or above	5	2.6	114	54.8	41	21.1	112	54.7
Paratransit job monthly income	<1 million Rp	165	85.9	66	31.7	57	29.4	29	14.1
	1–2 million Rp	17	8.9	112	53.8	132	68.0	107	52.2
	>2 million Rp			29	14.0	5	2.6	69	31.7
	Missing	10	5.2	1	0.5			4	2.0
Household monthly income	<1 million Rp	145	75.5	57	27.4	43	22.2	30	14.6
	1–2 million Rp	15	7.8	94	45.2	117	60.3	95	46.3
	>2 million Rp			55	26.4	31	16.0	79	38.6
	Missing	32	16.7	2	1.0	3	1.5	1	0.5
Living district	DKI Jakarta	22	11.5	121	58.2	183	94.3	143	69.8
	Other places	161	83.8	79	38.0	7	3.6	40	19.5
	Missing	9	4.7	8	3.8	4	2.1	22	10.7
Vehicle ownership	With a vehicle	97	50.5	201	96.6	2	1.0	24	11.7
	Without a vehicle	95	49.5	7	3.4	192	99.0	181	88.3
Number of paratransit drivers surveyed		192		208		194		205	

In terms of education level, *ojek* and *angkot* drivers clearly have similar levels of education, which is the highest among the four types of drivers and is followed by *bajaj* drivers and *becak* drivers in that order. Predictably, people with better education obtain better salaries, and this is seen in the order of paratransit job average monthly income (take home pay): *angkot* drivers > *ojek* drivers > *bajaj* drivers > *becak* drivers.

Residential districts of the four types of drivers reflect the current distributions of their businesses as paratransit drivers. The high percentage (83.8 %) of *becak* drivers living outside DKI Jakarta reflects the ban on *becak* businesses there, and only a few *becak* drivers struggle at the fringes. *Ojek* and *angkot* are quite common modes in the JMA, and the higher proportion of these vehicles in DKI Jakarta than in surrounding areas is partly attributable to both greater population density and survey location. However, the operations of *bajaj* drivers are only conducted in DKI Jakarta, which is indicated by the fact that 99 % of them live there.

Vehicle ownership clearly shows that approximately half of *becak* drivers own their own vehicle. As expected, almost all *ojek* drivers (96.6 %) own their vehicles, while most *bajaj* and *angkot* drivers do not—99.0 % and 88.3 %, respectively.

6.7.2 Paratransit Drivers' Responses to Policy Interventions

An SP survey was designed to explore a sustainable paratransit system from the viewpoint of drivers' job choices. The policy intervention is viewed from both social and environmental perspectives. Questions for drivers from the social perspective focus on the future availability of the respondent's current job (yes or no: "no" means that the job will be prohibited by the government), employment opportunity (two or three levels: defined as percentage of available job positions compared with the respondent's current job) and employment status (two options: self-employed vs. union member, employed by a company). From the environmental perspective, respondents are asked about vehicle fuel type (two forms: gasoline vs. CNG or electricity) and subsidy for low-emission vehicles (new vehicle types) (three levels: no subsidy, low and high levels). Other factors included in the SP design are operational costs of paratransit (two levels: low and high) and salary (two or three levels based on respondents' current salary). Monthly income is traded off against the saving in operational cost of new vehicles. It is expected that through such policy interventions, current paratransit drivers can be effectively persuaded to shift to new paratransit modes, so that the government can make a comprehensive and sustainable urban transportation plan to cover all transport services.

An orthogonal fractional factorial design results in 16 SP profiles, which are further randomly grouped into four balanced blocks. Each driver in the survey was only asked to answer one block with four SP questions, each of which includes two to four job options. Before each question, new types of jobs are briefly described, and expected salaries for various employment opportunities are calculated and shown in the questionnaire. The resulting sample size is 715 for *becak* drivers, 671 for *ojek* drivers, 684 for *bajaj* drivers, and 612 for *angkot* drivers. It is found that the majority of respondents prefer the same driver job with better conditions (*angkot* drivers: 51.2 %; *bajaj* drivers: 69.2 %; *ojek* drivers: 77.5 %), except *becak* drivers (74.3 % would prefer a job as a new *ojek* driver), and 44.7 % of *angkot* drivers would also prefer to be an *ojek* driver. This finding suggests that paratransit drivers are quite captive to their current jobs but desire to change their job conditions. This higher captivity also suggests that they have no other choices. Reflecting this observation, this study adopts the same dogit model (Gaudry and Dagenais 1979) as in Sect. 6.4.

The factors that are assumed to influence job choices are classified into job attributes and individual characteristics. The estimation results are shown in Tables 6.5 and 6.6. For four types of paratransit drivers, dogit models capture well their job choice behavior in response to the various assumed policy interventions in terms of goodness-of-fit indicators (adjusted McFadden's rho-squared at zero) ranging from 0.185 to 0.431. Dogit models further confirm that there is "a captive job" for each type of driver. *Becak* drivers, *ojek* drivers and *angkot* drivers have significant preferences for "new *ojek* driver" jobs, reflected by 90 % or higher confidence intervals, and *bajaj* drivers are significantly captive to "new *bajaj* driver" jobs, indicated by a 99 % confidence interval.

Table 6.5 Estimation results of *becak* drivers' and *ojek* drivers' stated job choice

Becak driver job choice			Ojek driver job choice		
Explanatory variable	Parameter	*t*-statistic	Explanatory variable	Parameter	*t*-statistic
Alternative specific constant			*Alternative specific constant*		
Ojek	−0.446	−0.364	Ojek	0.241	0.196
Bajaj (as reference)	–	–	Mix of Bajaj and Becak (as reference)	–	–
Current job	6.120	3.517	Current job	−4.896	−1.601
Ojek, Bajaj, current job			*Ojek, mix of Bajaj and Becak, current job*		
Operation cost	0.243	2.358	Operation cost	−0.277	−1.258
Employment status (1: union member; 0: self-employed)	0.950	1.218	Employment status (1: union member; 0: self-employed)	0.663	1.225
Employment opportunity	3.380	5.530	Employment opportunity	5.865	3.686
Salary	0.199	0.106	Salary	2.889	0.954
Fuel type (1: electricity for ojek; CNG for bajaj; 0: gasoline)	0.435	0.735	Fuel type (1: electricity for ojek; CNG for bajaj; 0: gasoline)	0.129	0.264
Subsidy	10.255	1.796	Subsidy	5.462	1.010
Ojek			*Ojek*		
Age	0.065	2.103	Marital status (1: married; 0: single)	−0.244	−0.473
Current job (Becak driver)			Age	0.009	0.279
Age	−0.141	−2.921	Household income (less than 1 million Rp)	−1.346	−2.719
Theta			Living in DKI Jakarta (1: yes; 0: no)	0.567	1.214
Ojek	0.795	3.100	*Current job (ojek driver)*		
Bajaj (as reference)	–	–	Marital status (1: married; 0: single)	−4.383	−2.290
Current job	0.000	0.005	Age	0.358	2.535
Log-likelihood at zero	−643.19		Household income (less than 1 million Rp)	−4.463	−2.496
Log-likelihood at convergence	−401.98		Living in DKI Jakarta (1: yes; 0: no)	−5.612	−2.601
McFadden's rho-squared at zero	0.375		*Theta*		
Adjusted McFadden's rho-squared at zero	0.356		Ojek	1.183	4.090
Sample size (SP profiles)	715		Mix of Bajaj and Becak (as reference)	–	–

(continued)

Table 6.5 (continued)

Becak driver job choice			Ojek driver job choice		
Explanatory variable	Parameter	*t*-statistic	Explanatory variable	Parameter	*t*-statistic
			Current job	0.161	2.462
			Log-likelihood at zero	−610.66	
			Log-likelihood at convergence	−329.18	
			McFadden's rho-squared at zero	0.461	
			Adjusted McFadden's rho-squared at zero	0.431	
			Sample size (SP profiles)	671	

Table 6.6 Estimation results of *bajaj* drivers' and *angkot* drivers' stated job choice

Bajaj driver job choice			Angkot driver job choice		
Explanatory variable	Parameter	*t-statistic*	Explanatory variable	Parameter	*t*-tatistic
Ojek, Bajaj, current job			*Ojek, medium bus, current job*		
Operation cost	−0.352	−3.23	Operation cost	−2.733	−2.53
Employment status (1: union member; 0: self-employed)	0.563	1.09	Employment status (1: union member/ company staff; 0: self-employed)	0.039	0.15
Employment opportunity	0.320	0.47	Employment opportunity	1.251	1.90
Salary	0.088	0.05	Salary	−4.273	−2.49
Subsidy	6.328	1.65	Fuel type (1: electricity for ojek, electricity/ CNG for medium bus; 0: gasoline)	0.079	0.38
Ojek			*Ojek*		
Fuel type (1: electricity; 0: gasoline)	−0.214	−0.46	Subsidy	−4.224	−1.48
Mix of Bajaj and Becak, current job (Bajaj driver)			Education level (high school and above)	−0.474	−1.42
			Living in DKI Jakarta (1: yes; 0: no)	−1.203	−2.64
Marital status (1: married; 0: single)	2.572	4.37	Household income (less than 1 million Rp)	−1.647	−1.48
Education level (secondary school)	−1.071	−3.16	Marital status (1: married; 0: single)	−0.563	−1.15
Education level (high school)	−2.066	−4.71	*Medium bus and current job* (Angkot driver)	–	–
Household income (less than 1 million Rp)	1.025	2.59	*Theta*		

(continued)

Table 6.6 (continued)

Bajaj driver job choice			Angkot driver job choice		
Explanatory variable	Parameter	*t-statistic*	Explanatory variable	Parameter	*t*-tatistic
Household income (1 million to 2 million Rp)	1.464	3.56	Ojek	0.471	1.859
Living in South DKI Jakarta (1: yes; 0: No)	−0.474	−1.19	Medium bus (as reference)	–	–
Living in East DKI Jakarta (1: yes; 0: No)	1.642	4.20	Current job	0.015	0.870
Fuel type (1: CNG; 0: gasoline)	−0.875	−1.35	Log-likelihood at zero	−549.09	
Theta			Log-likelihood at convergence	−435.75	
Ojek (as reference)	–	–	McFadden's rho-squared at zero	0.206	
Mix of Bajaj and Becak	0.517	2.75	Adjusted McFadden's rho-squared at zero	0.185	
Current job	0.000	0.00	Sample size (SP profiles)	612	
Log-likelihood at zero	−614.40				
Log-likelihood at convergence	−397.64				
McFadden's rho-squared at zero	0.353				
Adjusted McFadden's rho-squared at zero	0.327				
Sample size (SP profiles)	684				

As for job attributes, employment opportunities (from the social perspective) and subsidies for low-emission vehicles (from the environmental perspective) are predicted to play a significant role in job choices when paratransit drivers face various policy interventions in the future. Meanwhile, their individual characteristics also influence their job choice behaviors strongly. Among these characteristics, geographical location is regarded as a common significant influence on motorized paratransit drivers. Detailed explanations of each type of driver are given below.

1. Becak Drivers
   In the SP survey, 74.3 % of *becak* drivers chose to be new *ojek* drivers, 14.8 % chose to be new *bajaj* drivers, and nearly 10 % chose to keep their current jobs.

   The statistical significance of the parameters indicates that for the lowest socioeconomic group of paratransit drivers, the most important consideration may be to find work for subsistence, irrespective of wages, vehicle fuel type or employment status of that job in future. *Becak* drivers also pursue changes in their current jobs as motorized vehicle drivers to achieve a higher economic level (inferred from the 95 % significance in the parameter of operational cost). Because the operational costs of *ojek* and *bajaj* are much higher than that of

becak, the positive parameter sign shows the drivers' eagerness to change to a job with a motorized vehicle (but with higher operational costs). The significant *ojek*-specific captivity parameter (*Theta*) further reveals that the "new *ojek* driver" will be the captive job in future for *becak* drivers. It also implicitly confirms their desire to change their current jobs. The statistical significance and parameter sign of subsidies for low-emission vehicles show that *becak* drivers definitely need financial support to purchase a new vehicle. Certainly employment status, fuel type and wage also have positive effects on job choices, although their effects are not obvious (or significant).

As for individual characteristics, only age affects job choices. Older *becak* drivers tend to choose the "new *ojek* driver" job and are more reluctant to continue their current *becak* job.

2. Ojek Drivers

In the SP survey, 77.5 % of *ojek* drivers preferred the same job with better conditions, and only 11.3 % wished to continue their current job without changes.

The statistical significance and parameter sign of employment opportunity confirms the intense competition among *ojek* drivers and between *ojek* drivers and those in other types of paratransit jobs. First, *ojek* jobs have no entry limitation in the sense that anyone who has a motorcycle can engage in this illegal business. Second, *ojek* jobs are the captive jobs for *becak* drivers, *ojek* drivers and *angkot* drivers, as indicated by the statistically significant job-specific captivity parameter (*Theta*). The operational cost, which is quite low for an *ojek*, does not influence the choice of *ojek* driver job, and as a result, the financial saving from the lower operational costs of an electric-powered *ojek* compared with the much larger investment in the purchase of a new motorcycle is not attractive at all, a conclusion partially supported by the insignificant fuel type parameter. Presumably because of the high proportion of *ojek* drivers who own the vehicle, it is not surprising that subsidies for purchase of low-emission vehicles play no further important role. The inherent features of *ojek* jobs are that divers enjoy more freedom in work schedules and face intense competition, which may explain why they have low expectations with regard to wages and do not care about employment status.

In terms of individual characteristics, single *ojek* drivers tend to continue their current job, probably because they cannot afford new vehicles or they wish to save for marriage. Older *ojek* drivers express the intention to retain the current vehicle. *Ojek* drivers with the lowest level of household income (here, less than 1 million Rp) express a strong desire to change their current job, undoubtedly because of dissatisfaction with their current income level. *Ojek* drivers living in DKI Jakarta have an obvious desire to quit their current job in future. This could be because they realize that the living space of the current job is limited by the consistently improving public transportation system, serious pressure from the government in terms of punishing illegal *ojek* operation, and competition with other transport modes. For the "new *ojek* driver job" option, *ojek* drivers in the lowest income group show strongly negative attitudes toward their current jobs.

3. Bajaj Drivers
   In the SP survey, 69.2 % of *bajaj* drivers preferred the same job with better conditions, and only 4.0 % reported a desire to continue with no changes. It is interesting that the "new ojek driver" job is preferred by 25.0 % of the current *bajaj* drivers.

   Operational costs, directly determining the level of wages, significantly affect job choices. Although the subsidy for low-emission vehicles has an obvious impact on job choices, it cannot promote the use of low-emission vehicles with cheaper operational costs. This argument can be supported by two negative parameters of fuel type for the *ojek* and *bajaj*/*becak* job options. From this point, it can be inferred that the subsidy for low-emission vehicles is insufficient and/or the savings in operational costs from vehicle changes cannot compensate for the enormous cost of purchasing the low-emission vehicles (*ojek* is electrically powered, and *bajaj* is CNG powered). Another possible reason is that *bajaj* drivers underestimate the performance of such vehicles because of their unfamiliarity. If this is true, the advantages of low-emission vehicles should be properly publicized.

   Looking at the influence of individual characteristics, married *bajaj* drivers have an obvious tendency to choose "new *bajaj* driver" jobs. The higher the education level, the lower the desire to choose a "new *bajaj* driver" job. *Bajaj* drivers with lower household income (less than 1 million Rp and between 1 and 2 million Rp) prefer a "new *bajaj* driver" job. *Bajaj* drivers from East Jakarta are more likely to choose the *bajaj*/*becak* option. The statistically significant captivity parameter (*Theta*) clearly indicates that current *bajaj* drivers would like to have their own *bajaj* and to do this job in the future; that is, they would be captive to new *bajaj* jobs.
4. Angkot Drivers
   In the SP survey, 51.2 % of *angkot* drivers preferred the same job with better conditions, and only 4.1 % expressed a wish to continue their current job without changes. It is interesting that 44.7 % of current *angkot* drivers preferred a "new *ojek* driver" job in future.

   The job salary parameter is statistically significant and negative. This suggests that *angkot* drivers prefer a "new *ojek* driver" job, even though the salary level is lower. A possible explanation is that current *angkot* drivers without their own vehicle would like their own *ojek* first so that they can enjoy the more flexible work style of an *ojek* job at the expense of some of their wage. Meanwhile, the statistically significant job-specific captivity parameter (*Theta*) for *ojek* also suggests that 44.7 % of current *angkot* drivers would prefer "new *ojek* driver" jobs in the future. The employment opportunity positively influences job choice. The insignificant influence of fuel type can be partially explained by the negative parameter of subsidy for a low-emission vehicle.

   With respect to individual characteristics, the only statistically significant dummy variable (living in DKI Jakarta) shows clearly that *angkot* drivers from DKI Jakarta are reluctant to take *ojek* driving as a future job option.

5. Summary
   Recognizing the important roles played by paratransit systems in providing valuable job opportunities to low-income people and quite seamless transport services to residents in developing cities, this study has attempted a comprehensive investigation of the employment issues of paratransit drivers in developing cities by taking the JMA as an example. Drivers of four typical paratransit vehicles (*becak*, *ojek*, *bajaj*, and *angkot*) were targeted. Aiming to create more competitive, attractive and sustainable paratransit systems in future, this study examined whether current paratransit drivers would prefer new and different paratransit driver jobs in vehicles equipped with low-emission vehicles under altered competitive employment circumstances as well as various policy interventions. "Captive jobs" are identified, especially for jobs as *ojek* and *bajaj* drivers. It is also revealed that employment opportunities reflecting the social perspective of policy interventions, and government subsidies for low-emission vehicles reflecting the environmental perspective, have strongly contrasting influences on the job choices of four typical types of paratransit drivers. For policy-related variables, only subsidies for new vehicles exert a significant influence on *becak* and *bajaj* drivers' job choices. Given the current energy subsidies in Indonesia, it seems that fuel type has almost no impact on the job choice behavior of paratransit drivers. This suggests that financial incentives are the most important tool for encouraging paratransit drivers to shift to sustainable driver jobs. In contrast, savings from the operational costs of vehicles with much cleaner power seem to have no influence on drivers' job choices. To the best of the authors' knowledge, this is the first comprehensive study in the transportation literature to examine factors affecting the job choices of various types of paratransit drivers under social and environmental policy interventions. These analysis results offering deep insight into job choices of paratransit drivers could be useful for decisions on policies to transform the current ineffective paratransit systems in developing cities to make transportation more sustainable, competitive and attractive.

6.8 Conclusions and Future Challenges

6.8.1 Policy Design for Paratransit-Adaptive Transportation Systems

The popularity of paratransit in developing countries is undoubtedly supported by local people's various mobility needs. Many existing case studies in various parts of the developing world, including ours, have confirmed this popularity. Paratransit in developing countries is currently an essential travel mode because of inadequate official public transportation systems. Until such needs can be satisfied by official public transport services, paratransit will continue to be an indispensable part of transportation systems in developing countries. The case studies in this chapter revealed unique policy directions for redesigning the paratransit systems in developing countries according to their users' travel behavior, drivers' job choices and QOL considerations of both users and drivers.

First, paratransit issues concern not only transportation but also society. We reconfirmed this point with a series of systematic and consistent questionnaire surveys. It is suggested that paratransit policies should be decided by systematically evaluating the influence of policies on people's QOL. Unfortunately, in reality, discussions about sustainable transport policies in developing countries have ignored, or at least attached less importance to, the social equity issues related to paratransit. According to a speech by the mayor of Surabaya City,[1] it is planned that angkot drivers' in Surabaya City will have their wages paid, and will be provided with new types of vehicles, by the government. Many development aid programs by international agencies have mainly focused on strategic planning of transportation systems in developing countries without sufficient attention to issues in the transitional process. Surabaya's practices should be evaluated carefully if the plan is realized. To make such policies possible, strong leadership is definitely required, because various governmental sectors, including the transportation sector, need to collaborate. In reality, such cross-sector collaboration is very important but is always the most difficult aspect of implementing policies. To demonstrate leadership, effective cross-sector collaboration frameworks should be established.

Second, this study emphasizes the importance of behavioral studies in transport policy decisions. Recently, in recognition of the limitations of supply-oriented policies in resolving transportation issues, a new approach, called the A–S–I (A: Avoid/Reduce, S: Shift/Maintain, I: Improve) approach, was proposed to achieve reductions in GHG emissions, energy consumption and congestion, with the final objective of creating more livable cities.[2] The avoid–shift–improve (ASI) approach aims to *mitigate* the impacts of transportation activities. However, this is insufficient to address environmental issues involving paratransit. Insufficient official transportation services have pushed increasing numbers of people in developing countries to rely heavily on it. Simply eliminating it from transportation systems in developing countries may resolve environmental issues but at the same time will surely result in more social issues caused by unemployment among paratransit drivers and may erect barriers to the transportation poor, whose only available (and/or affordable) means of travel may be paratransit. Therefore, measures adapted to paratransit should be taken jointly with these mitigation measures.

The above observations suggest that for transition to sustainability during the current economic development in developing countries, a considerable period of regulating and incorporating paratransit into official public transportation systems rather than simply banning it is a wise method for realizing sustainable urban transportation.

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[1] An invited speech given by Ms Tri Risnaharini, the Mayor of Surabaya City, in the GELs Special Seminar on Urban and Regional Development in Climate Change Regime, organized by the Hiroshima Center for International Environmental Cooperation (HICEC), Hiroshima University, November 19, 2012.

[2] www.sutp.org

6.8.2 Recommendations for Future Research

This study comprehensively examines issues of paratransit systems in developing countries from the perspectives of supply and demand as well as QOL of paratransit drivers and users. Various new findings and potential policies for transition to sustainability have been proposed. However, there are still many issues that need to be addressed to put our findings into practice.

First, to generalize our findings, more case studies should be conducted on large-scale questionnaire surveys in various parts of the developing world. Second, regarding choice behavior in terms of paratransit drivers' job choices and users' travel mode choices, heterogeneous responses to policies should be combined to promote paratransit-adaptive transportation policies in developing countries effectively. To quantify the effects of transportation policies on QOL, travel behavior requires investigation together with other aspects of citizen's life behavior, and a comprehensive QOL evaluation model system should be developed linking policy to behavior decisions, and behavior decisions with QOL evaluations (Zhang et al. 2012).

Second, the above behavioral studies should be incorporated into a framework of transportation network analysis covering both demand and supply sides of paratransit as well as official transportation systems. It is relevant to this transportation network analysis that Anwar et al. (2011) and Weningtyas et al. (2012b) confirmed that the reduction of travel speed resulting from traffic congestion in Dhaka, Bangladesh and Bandung, Indonesia can be observed at much lower ratios of traffic volume to capacity than in developed countries. Such remarkable reductions in travel time are largely because of mixed paratransit and official transportation vehicle traffic, on-street parking and shops. Such travel time performance has not been reflected well in transportation network analyses of developing countries. Furthermore, redesign of paratransit systems in developing countries requires clear policy goals, which should be incorporated into the process of transportation network design (Weningtyas et al. 2012c). For this purpose, it is worth developing a hybrid network analysis framework with both top-down and bottom-up decision-making mechanisms, in which various sustainable urban and transportation policy scenarios can be systematically and consistently examined (e.g., Feng et al. 2010; Feng and Zhang 2012).

Third, to resolve the traffic issues caused by paratransit in developing countries, mitigation measures are definitely required. However, considering the special situations in developing countries, transportation policy decision makers need to pay attention to paratransit and its popularity. Paratransit-adaptive measures must be taken to enhance the public acceptance of policies. There is no doubt that in reality, both mitigation and adaptation measures are required, but the success of mitigation measures relies heavily on whether appropriate alternative travel options can be provided. It is important to clarify how best to package the mitigation- and adaptation-oriented measures under the constraints of financial budgets and limited human resources. Because the social impacts of paratransit policies seem remarkable, the transportation sector should collaborate well with other relevant governmental sectors under a better governance scheme.

Finally, international agencies and other donors should exert their best efforts to assist recipients' endogenous development based not only on easily applied but old-fashioned and less scientific methods but also on up-to-date scientific methods by adapting them to local contexts. In the paratransit context, the above scientific approaches should be developed based on cutting edge international knowledge and local expertise.

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Chapter 7
Tourist Behavior Analysis for Sustainable Tourism Policy

Lingling Wu, Junyi Zhang, and Akimasa Fujiwara

Abstract Tourists' travel decisions usually involve a number of choices made over time and across space. Because tourists face many aspects of choices and must deal with spatial and temporal constraints, it is expected that there will be interdependences in their behavior. Accurate representation of such interdependences is essential for improving understanding of their behavior and consequently may provide insights into tourism marketing and policy decisions. This chapter investigates interdependences among several aspects of tourists' travel decisions, aiming to provide behavioral foundations for the development of an integrated tourism model system. It introduces two studies concerning integrated tourist behavior modeling. The first study jointly analyzes tourists' three interrelated choices by using a nested logit (NL) model. In the second study, tourist's time-use behavior, involving multiple activities, is analyzed using a multiple discrete–continuous extreme value (MDCEV) model. Application analyses are conducted using data collected in Japan. The findings have important practical implications for both destination management and policy making.

Keywords Integrated modeling • Interdependence • MDCEV model • Nested logit model • Tourist behavior

7.1 Importance of Tourist Behavior Analysis

UNWTO (2006) identified 15 megatrends of tourism in the Asia-Pacific region in the year 2006, of which more than half are directly related to tourist behavior. First, tourists tend to prefer activity- and interest-based travel to destination-based travel. At the

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same destination, tourists usually participate in the same activities according to the major tourism resources available, but they may be interested in and participate in other types of activities. This emphasizes the importance of understanding tourists' activity participation and time use at destinations. Second, tourists' tastes and travel spending are becoming polarized in the sense that some visitors seek comfort and/or luxury travel products, while others desire thrills and/or budget travel. Catering for heterogeneous traveling tastes and budget decisions is therefore of increasing importance. Third, tourists are more likely to pay for travel experiences than for products. Such experience-oriented consumer behavior has been observed in the more general marketing context (see Drotskie 2012). Fourth, rapid growth of business travel is expected, suggesting that exploring tourism demand generated by business trips is important.

The final trend in tourism results from growth in the number of seniors and women travelers. Travel safety and health will become major concerns for these tourists. This final trend supports the role of group package tours but at the same time encourages marketers of group package tours to consider these tourists' heterogeneous traveling tastes and budget decisions carefully. Review of the megatrends related to tourist behavior suggests that understanding tourist behavior is not merely of academic interest but is essential for effective tourism planning and policy making. To propose effective policies, it is necessary to understand how tourists make decisions. Better understanding of tourist behavior would provide information about how and when policy interventions are needed to obtain desirable results. Specifically, research concerning tourism participation behavior offers useful information on encouraging people to make full use of their free time to participate in tourism activities. A better understanding of tourist behavior during travel is essential for policy makers and destination planners to provide tourists with high-level services. Experiences during travel are the major factor influencing tourist satisfaction, and these in turn influence their intention to return and/or to recommend the destinations to other people. Therefore, providing tourists with good services is crucial for tourism marketers. At the same time, the public sector must provide high-quality infrastructure (e.g., convenient transportation networks, attractive transit malls in city centers and accessible tourist facilities) and public services (e.g., an uncongested driving environment and friendly tourist information centers) that can facilitate tourism. Thus, understanding tourist behavior is very important for both the public and private sectors.

7.2 Environmental Significance of Tourist Behavior

A considerable proportion of global passenger transport is linked to tourism activities, in which more than 10 % of the world's population participate annually (Budeanu 2007). The tourism industry is therefore of interest to those studying transport-related environmental problems and sustainable transport systems.

The environmental problems generated by tourism are related to various aspects of tourist behavior. Specifically, the temporal imbalance (especially the concentration) of tourism generation usually raises serious problems such as air pollution and traffic congestion during peak seasons. Overcrowding of popular destinations creates environmental pollution and leads to overexploitation of local resources and overuse of tourism facilities. Related to destination choice are travel mode and route choices, which contribute to traffic congestion and air pollution. At destinations, tourists' on-site activities may also have a negative impact through resource consumption, waste generation, and facility overuse. Travel experiences are major influences on tourists' posttravel evaluations. Such evaluations influence future tourist behavior.

The overview of the environmental impact of tourist behavior suggests the complexity of measures to achieve sustainable tourism development. It is necessary to propose a combination of policies to address the diverse impacts of tourism. In addition, because the various dimensions of tourist behavior interact, any given policy influences the whole choice process and its resulting environmental impacts. To obtain an accurate evaluation of the policy effect, a comprehensive view of the whole tourism process before, during and after travel is required.

7.3 Framework of Tourist Behavior Analysis

Tourist behavior plays an important role in influencing tourism development and whether its interaction with the environment is positive or negative. It is therefore essential to gain a thorough understanding of tourist behavior to provide appropriate insights into tourism policy decisions.

Tourists' travel decisions usually involve a number of separate but interdependent choices over time and across space. Recently, a growing number of studies have been conducted focusing on different aspects of tourist behavior, such as tourism participation (Alegre et al. 2010), destination choice (Nicolau and Mas 2008), travel mode (Kelly et al. 2007) and route choice (Fujiwara and Zhang 2005; Lew and McKercher 2002), length of stay (Barros and Machado 2010; Thrane 2012), and activities during travel such as shopping and dining (Kemperman et al. 2009). However, because tourists face many choices and have to deal with spatial and temporal constraints and a degree of uncertainty, it is argued that tourist choice behavior is a multidimensional process and that decisions about these dimensions of behavior are interdependent (Dellaert et al. 1998).

Therefore, to gain a thorough understanding of tourist behavior, it is necessary to represent these interdependences systematically and logically and to incorporate choice aspects into a system. The most systematic framework of tourist behavior analysis so far has been proposed by Woodside and Dubelaar (2002). They conceptualized a framework that consists of a multiphase process starting with information search and use, followed by travel to a destination, on-site experiences and activities, and posttravel evaluation. However, relevant research focusing on the integrated modeling of tourist behavior is currently very limited.

Under such circumstances, this study attempts to construct a model system incorporating all the major choice aspects of tourist behavior and taking all

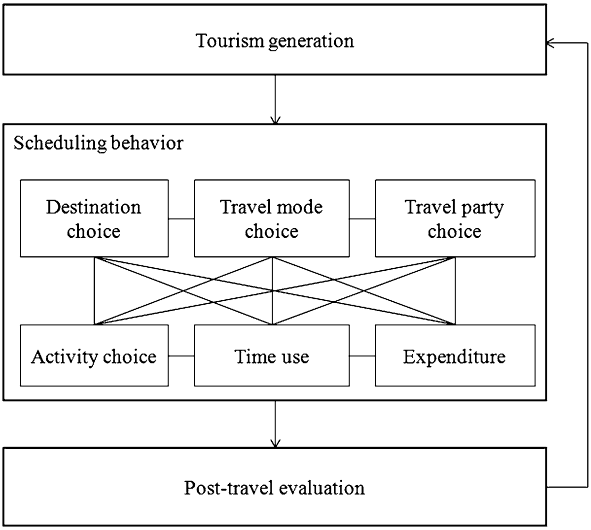

Fig. 7.1 Framework of tourist behavior analysis

multifaceted dependences and interactions into account. Figure 7.1 shows the framework for this study.

In the first stage, individuals recognize a need and are motivated to participate in tourism. A variety of factors influence this participation, including individual and environmental factors (Crompton and Ankomah 1993). The former include individual demographics, personality traits, lifestyles, values and emotions, while the latter are external factors including social, cultural, and market variables. All of these factors shape individuals' tourism motivation and have an impact on their decision to participate in tourism.

Subsequent to this decision is scheduling behavior, which involves a variety of choice aspects. To illustrate these aspects of behavior, we classify them into several dimensions: spatial choice, resource allocation, and social contexts.

Spatial choice usually has several levels according to spatial scale. Some choices are made before travel (e.g., destination, travel mode, and accommodation), while others are usually made during travel (e.g., route, and activities during travel, such as shopping and dining). As Seddighi and Theocharous (2002) have mentioned, a spatial choice needs a multistep decision-making process. A tourist is usually faced first with several destination alternatives when deciding to travel, and when that is determined, with a choice of travel mode. Although these choices can be made at different times, they may interact. Outcomes of first choices may influence subsequent choices. For example, a tourist first chooses a destination and then chooses accommodation considering prices and hotel room availability at the destination.

Time and money are the main resources for travel activities. Because of the availability and scarcity values of these two resources, participation in various activities is constrained. Resource allocation decisions include both long-term and short-term aspects. Long-term decisions concern when to travel, how long to stay and how much to spend. Short-term decisions are mainly those made when traveling (time and money allocation). Because of limited time and finance, tourists must arrange and participate in the planned activities in a satisfactory order at a satisfactory time and must allocate a satisfactory length of time and amount of money to derive maximal satisfaction. Resource allocation behavior can directly constrain or expand the number and range of potential activities and the intensity to which individual activities can be experienced (Pearce 1988). Because the planned activities are usually conducted in different places, constraints of available time and money may result in various interactions between spatial choice and resource allocation behavior.

Social contexts refer to whether and how tourists decide to travel with other people. If traveling with other people, tourists must be influenced by coupling constraints, which refer to the necessity for remaining with companions at a specific place and point in time. Another aspect of social contexts is that tourism decisions usually involve some group decisions, especially in the case of travel with other people (e.g., family members, friends, and colleagues).

After traveling, tourists will evaluate their trip. Experiences during travel are the major factors influencing these evaluations. Postconsumption evaluations result in a feeling of satisfaction or dissatisfaction (Westbrook and Oliver 1991), which strengthens or weakens attitudes toward the destinations visited and may in turn affect expectations for future visits (Kozak 2001). The tourists may also communicate information on their experiences to people around them (word-of-mouth information).

This study aims to incorporate all the major choice aspects related to tourist behavior into an integrated system (Fig. 7.1), which will contribute to a better understanding of complexity and interdependences involved in tourist behavior. It is expected that the result will enable policy makers to evaluate the effectiveness of policies in a systematic way.

7.4 Case Studies in Japan

In Japan, the site of this case study, the tourism industry directly and indirectly generated 7.5 % of GDP and 9.6 % of jobs in the year 2009 (Japan Tourism Agency 2010). In addition to its tremendous economic impact, the tourism industry has also contributed to infrastructure development, regional revitalization and cooperation. Especially in recent years, rural areas in Japan have suffered from depopulation. The development of the tourism industry in these rural areas supports those who have suffered from the negative effects of depopulation. However, the development of the tourism industry has also caused serious environmental problems. Because many people in Japan choose to travel during Golden Week (also called Large Consecutive Holiday, which is a collection of four national holidays within 7 days between the end of April and the beginning of May), the temporal imbalance (especially the concentration) of tourism demand usually causes serious traffic congestion, overuse of tourism resources and damage to natural features.

For the purposes of achieving sustainable development of tourism industry, the "Tourism Nation Promotion Basic Law" was enacted in January 2007, and the Japanese government developed the "Tourism Nation Promotion Basic Plan" as a master plan for a tourism nation to promote various measures in a comprehensive and systematic manner. The plan proposed various policies to revitalize tourism development and to minimize negative environmental impacts at the same time. In this chapter, two case studies will be introduced to analyze tourist behavior related to these policy issues.

In the first case study, a dynamic analysis is conducted to represent three stages of tourists' choices: tourism participation, destination, and travel mode. In Japan, encouraging participation in domestic tourism has been a central political issue for many years. On the other hand, visits to domestic tourist destinations have followed an unbalanced regional trend. At the same time, various transport policies have been proposed to encourage travel. Under such policy considerations, it becomes important to represent tourism participation, destination choice and travel mode choice in combination. However, tourism demand shows monthly variations. To date, the above three aspects of tourism have not been satisfactorily analyzed in a dynamic fashion. Aiming to provide a better understanding of interrelated tourist behavior and a scientific tool to support tourism policy decisions, this study jointly analyzed the above three aspects of tourists' choices by building a dynamic nested logit (NL) model that takes the influence of state dependence into account.

The second case study focuses on tourists' time allocation decisions concerning various activities during travel. Careful reviews suggest a lack of temporal studies in the field of tourism research, including its long-term aspects (e.g., period, life cycle, and cohort effects) and short-term aspects (e.g., duration and timing) (Zhang et al. 2006). Therefore, recognizing the importance of developing an integrated tourism behavior model, this study focuses on the poorly represented temporal aspects of tourists' behavior, especially decisions about time allocation for activities during travel. Understanding tourists' time-use decisions is useful for transport decisions on improvements in transport services for convenient participation in activities and the effective use of time allocated to activities. Because different tourism activities have different impacts on the environment, investigation of tourist's time use during travel could provide a tool to estimate the overall environmental impact of tourism activities.

7.4.1 Case Study 1: Dynamic Analysis of Three-Stage Tourist Choices

Tourists' travel decisions usually involve a number of choices made over time and across space (Dellaert et al. 1998), including whether to participate in tourism, where to go (destination choice), how to go (travel mode choices), and with whom to go (travel party choice). Although the above choices can be made at different times, they may interact. Outcomes of first choices may influence subsequent choices. Therefore, tourists' choice behavior should be regarded as a multistage choice process that consists of a number of separate but interrelated choices. Furthermore, tourist behavior may be interrelated over time and may show state dependence. In other words, tourists' previous behavior may influence current behavior. The purpose of this study is to analyze tourists' three interrelated choices (whether to travel, destination, and travel mode) jointly and to examine the influences of state dependence and other factors on these three choices.

7.4.1.1 A Nested Logit Model with Three Levels

In this study, tourist behavior is analyzed over a 1-year period divided into 12 waves (each month is a wave). In each wave, tourism participation, destination choice and travel mode choice are jointly analyzed using a nested logit (NL) model. The NL model has often been applied to incorporate logically interdependence among the behavioral elements with the help of expected maximal utility (i.e., a logsum variable or inclusive value). In this study, the nesting structure is assumed to include tourism participation choice at the first level, destination choice at the second level, and travel mode choice at the third level. The joint probability of an individual's choice at wave t can be described as:

$$P_{nt} = P_{nt}(y)P_{nt}(d|y)P_{nt}(j|d) \tag{7.1}$$

where $P_{nt}(y)$ is the marginal probability of tourism participation, $P_{nt}(d|y)$ is the conditional probability of destination d being chosen given participation, and $P_{nt}(j|d)$ is the conditional probability of travel mode j being chosen given destination d.

The third-level travel mode choice probability follows a standard multinomial logit equation and can be represented as:

$$P_{nt}(j|d) = \frac{exp(V_{jt} / \theta_d)}{\sum_{j'} exp(V_{j't} / \theta_{d'})} \tag{7.2}$$

where V_{jt} represents the observable components of the utility function of travel mode j in wave t, and θ_d is the scale parameter associated with the nest of destination d. θ_d should be located in the interval (0, 1). A larger value of θ_d suggests greater influence of travel mode choice on the choice of destination d and weaker substitution of travel mode choice conditioned on destination d.

The observable components of the utility of travel mode choice V_{jt} are specified as:

$$V_{jt} = \alpha_{jt} + \lambda_j y_{jt'} + \sum_h \beta_h v_h \tag{7.3}$$

where α_{jt} is constant term for travel mode j in the tth wave, $y_{jt'}$ represents whether travel mode j was used in the previous trip, and v_h is the hth attribute describing travel mode choice.

The second-level destination choice probability can be derived as:

$$P_{nt}(d|y) = \frac{exp((V_{dt} + \theta_d \Gamma_{dt}) / \theta_p)}{\sum_{d'} exp((V_{d't} + \theta_d \Gamma_{dt'}) / \theta_p)} \tag{7.4}$$

$$\Gamma_{dt} = log(\sum_{j'} exp(V_{j't} / \theta_{d'})) \tag{7.5}$$

where V_{dt} represents the observable components of the utility function of destination d in wave t, Γ_{dt} is the logsum variable (or inclusive value) associated with the nest of destination d, and θ_p is the scale parameter associated with the nest of tourism participation.

The observable components of the utility of destination choice V_{dt} are specified as:

$$V_{dt} = \lambda_d y_{dt'} + \sum_g \beta_g X_g \tag{7.6}$$

where $y_{dt'}$ represents whether destination d was visited in the previous trip, and X_g is the gth attribute describing destination d.

Then tourism participation and nonparticipation probability in wave t can be derived as:

$$P_{nt}(y=1) = \frac{exp(V_{pt} + \theta_p \Gamma_{pt})}{1 + exp(V_{pt} + \theta_p \Gamma_{pt})} \tag{7.7}$$

$$P_{nt}(y=0) = 1 - P_{nt}(y_{nt} = 1) \tag{7.8}$$

$$\Gamma_{pt} = \log(\sum_{d'} \exp((V_{d't} + \theta_d \Gamma_{dt'}) / \theta_p)) \tag{7.9}$$

where V_{pt} is the observable components of the utility function of tourism participation in wave t, and Γ_{pt} is the inclusive value associated with the nest of tourism participation.

The observable components of the utility of tourism participation V_{pt} are specified as:

$$V_{pt} = \alpha_t + \lambda_p y_{p(t-1)} + \sum_s \beta_s z_s \tag{7.10}$$

where α_t is the constant term for the tth month, $y_{p(t-1)}$ is a dummy variable representing whether tourism participation occurred in the $(t-1)$th month (1, if occurred; 0, otherwise), and z_s is the sth explanatory variable.

The log-likelihood function is given as follows:

$$LogL = \sum_{n=1}^{N} \sum_{t=1}^{T} \ln((P_{nt}(y=1) \times (P_{nt}(d|y) \times P_{nt}(j|d)^{\delta_{jt}})^{\delta_{dt}})^{\delta_{nt}} \times P_{nt}(y=0)^{1-\delta_{nt}}) \tag{7.11}$$

where N indicates the total number of samples; T is the number of waves (equal to 12 in this case); δ_{nt} is a dummy variable that equals 1 when individual n participates in tourism in the tth wave, otherwise 0; δ_{dt} is a dummy variable that equals 1 when individual n chooses destination d in the tth wave, otherwise 0; and δ_{jt} is a dummy variable that equals 1 when individual n chooses travel mode j in the tth wave, otherwise 0. The resulting model can be estimated using a standard maximum likelihood estimation method.

7.4.1.2 A Web-Based Nation-Wide Tourist Behavior Survey

For the purposes of this study, we conducted a web-based questionnaire survey in Japan in April 2010 with the help of an Internet survey company, who had more than 1.4 million registered panels at the time of survey. Respondents were randomly selected from the registered panels according to the distributions of age, gender, and residential areas (prefectures) across the whole population in Japan.

The survey included very detailed information on individual tourism behavior in 2009. Respondents were first asked whether they had been on a holiday trip of more than one night in 2009. If the answer was yes, the respondents were asked specific questions about their tourism behavior in every month, including destination choice, travel date, motivation, travel mode, travel time, number in party, duration of stay, expenditure, and satisfaction. Sociodemographic data were also collected, including gender, age, occupation, education level, annual income, marital status, household composition, residential area, and car ownership. As a result, responses to 1,253 questionnaires were obtained.

The data characteristics are summarized in Table 7.1. It was observed that 64.0 % of the respondents were married, 46.4 % had a university degree, 51.8 % were employed, and 77.2 % had a private car. Table 7.1 also shows the distribution of travel frequency for each month and the whole year. Because we focus on domestic tourism in this study, information about international travel was eliminated. It can be seen that 25 % of the respondents took one tourist trip in the year 2009, and 40.5 % took more than one trip. In total, 65.5 % of the respondents participated in tourism during the whole year. The tourism participation percentage in each month is highest in August (19.6 %) and lowest in February (7.6 %). The percentages in May, September and October are quite high (around 15 %), while those in January and June are quite low (below 10 %).

In the survey, the destination alternatives are 47 prefectures in Japan. In this study, the 47 prefectures are further categorized into 18 zones based on geographical vicinity for the sake of model estimation (extremely low shares for some prefectures are avoided). Figure 7.2 gives a map of 18 zones.

Travel mode choice includes five alternatives: aircraft, *Shinkansen* (bullet train), railway, bus and car. Figure 7.3 shows the travel mode choice percentages to 18 destinations. We can see that aircraft is the dominant mode (97.7 %) to destination 18. As Okinawa prefecture is an island located separately from other parts of Japan, the surface travel modes are not available to get there. Likewise, destination 1 (Hokkaido

Table 7.1 Summary of data characteristics

Individual characteristic	Percentage	Travel frequency		Percentage
Gender	–	January	0	91.9
Male	49.6	–	1	7.6
Female	50.4	–	>1	0.5
Age	–	February	0	92.4
<30 years old	20.3	–	1	7.1
30–50 years old	34.0	–	>1	0.5
>50 years old	45.7	March	0	87.5
Occupation	–	–	1	11.9
Employed	51.8	–	>1	0.6
Student	3.5	April	0	88.7
Housewife	21.5	–	1	10.6
Others	23.2	–	>1	0.7
Education level	–	May	0	84.1
Having a university degree	46.4	–	1	15.1
Having no university degree	53.6	–	>1	0.8
Marital status	–	June	0	91.3
Single	36.0	–	1	8.5
Married	64.0	–	>1	0.2
Household income	–	July	0	88.4
<3 million yen/year	19.2	–	1	11.1
3–8 million yen/year	56.3	–	>1	0.5
>8 million yen/year	24.5	August	0	80.4
Household size	–	–	1	18.3
1 member	18.1	–	>1	1.3
2 members	28.4	September	0	85.2
3 members	24.9	–	1	14.0
>3 members	28.6	–	>1	0.8
Car ownership	–	October	0	84.3
Have a private car	77.2	–	1	14.8
Have no car	22.8	–	>1	0.9
Travel companions	–	November	0	86.0
Travel alone	13.2	–	1	13.4
Travel with others	86.8	–	>1	0.6
Travel motivation	–	December	0	86.2
Nature motivation	68.6	–	1	12.6
Culture motivation	29.7	–	>1	1.2
Shopping motivation	48.2	Whole year	0	34.5
Sport motivation	6.0	–	1	25.0
–	–	–	>1	40.5

prefecture) is an island located at the north end of Japan, and it is difficult for tourists from other places to get there by surface modes. On the mainland of Japan (destinations 2 to 17), car is the main travel mode for most of the destinations except 6, 7, 13 and 14. Because these destinations cover three important cities—namely, Tokyo, Kyoto and Osaka—the public transport systems in these regions are well developed.

Fig. 7.2 Map of destination alternatives

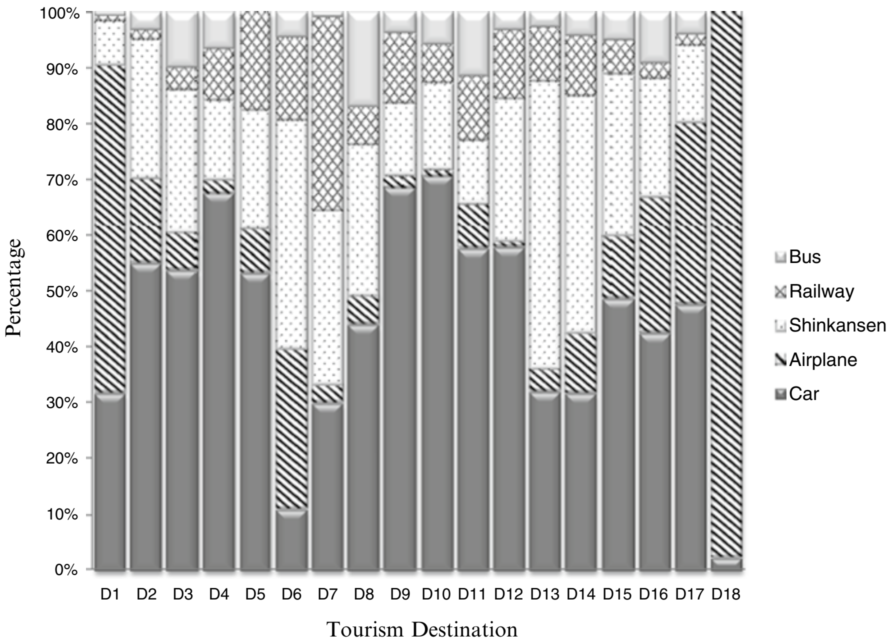

Fig. 7.3 Travel mode choice percentages to 18 destinations

Of travel mode choice percentages over 12 months, private car is the most popular travel mode for holiday trips, accounting for 30–50 % over 12 months. Especially in May, August and October, almost half of tourists choose to travel by car. The second most popular mode is aircraft, with a 20–36 % share over 12 months. In contrast to car, the aircraft share is lower in May, August and October than in other months. A considerable number of tourists choose to travel by *Shinkansen*, and this share is stable over 12 months (around 20 %). The least common travel modes are railway and bus. The shares for these two modes are around 8 % and 5 %, respectively.

7.4.1.3 Explanatory Variables

Based on the literature and previous research, variables including age, marital status, education level, household size, annual income, car ownership, and length of holiday are used as variables to explain utility of tourism participation in this study.

In this study, destination choices are combinations of prefectures. The appropriate attributes for large-scale tourism analysis are used as explanatory variables to describe destination choice, such as density of natural parks, cultural facilities, department stores, and sports facilities, in addition to number of tourist arrivals and festivals held in the destination. In previous research, tourism motivation is confirmed to have a significant influence on destination choice. This study includes motivation factors in the model as interaction terms with destination-specific attributes by assuming that tourists with a particular motivation will pay attention to a certain characteristic when they choose a holiday destination.

For travel mode choice, age, travel with others (yes or not), travel time and cost are used as explanatory variables. It is assumed that older people and tourists who travel with others are more likely to choose private car. The list of explanatory variables is given in Table 7.2.

7.4.1.4 Clarifying Behavioral Mechanisms and Factors

Estimation results are presented in Table 7.3. It can be seen that parameters of most of the explanatory variables are statistically significant at the 90 % or 95 % levels. Model accuracy is good enough to show the effectiveness of the model (i.e., McFadden's rho-squared is 0.64).

1. State Dependence

   The parameter of state dependence in tourism participation choice is negative. This result indicates that participation in tourism during month $t-1$ has a negative influence on participation during month t. This first confirms that tourism participation behavior surely depends on past behavior and then suggests that participation in a given month reduces the probability of participation in the following month.

   For destination choice, state dependence shows positive influence. Because the destination alternatives in this study are prefectures, the positive parameter for state dependence does not necessarily mean that tourists tend to

Table 7.2 Explanatory variables: nested logit model

Tourism participation	
Age	Actual age
Married	1: married; 0: otherwise
Education	1: having a university degree; 0: otherwise
Household size	Number of household members
Income	Annual household income (Million yen/year)
Car ownership	1: having a private car; 0: otherwise
Holiday	Length of statutory holiday in wave t
Destination choice	
Tourist arrivals	Tourist arrivals to destination d in wave t
Festival	Number of festivals hold in the destination d in wave t
Household size × distance	Number of household members × distance from residential area to destination d
Nature motivation × density of nature park	Dummy variable for whether or not have nature tourism motivation × area of natural park per km^2 in destination d
Culture motivation × density of culture facilities	Dummy variable for whether or not have culture tourism motivation × number of culture facilities per km^2 in destination d
Shopping motivation × density of department stores	Dummy variable for whether or not have shopping motivation × number of department stores per km^2 in destination d
Sport motivation × density of sport facilities	Dummy variable for whether or not have sport motivation × number of sport facilities per km^2 in destination d
Travel mode choice	
Age	Actual age
Travel with others	1: travel with others; 0: travel alone
Travel time (hours)	Travel time from residential area to destination by mode j
Travel fee (thousand yen)	Travel fee from residential area to destination by mode j

make repeated visits to exactly the same tourism attractions. They may acquire information about the area on an initial visit and return in a subsequent trip to visit places that were planned but not visited on the previous tour.

In terms of travel mode choice, the parameters of state dependence for all five alternatives are positive, which suggests persistence in tourists' travel mode choices. This kind of persistence is especially notable in the choice of bus but less so in the choice of aircraft.

2. Inclusive Value Parameters
The estimated inclusive value parameters are all between 0 and 1, and it is especially notable that most of the parameters are statistically different from both 0 and 1 at the 90 % or 95 % level. These statistical test results suggest that the NL model is applicable for this study. Larger values of these parameters suggest greater influence of choice behavior on the lower level rather than the upper level and decreasing substitution among alternatives in the nest. The estimated inclusive value parameters for destination choice suggest that tourists' choices of some destinations are influenced more strongly by travel mode choice. Taking Hokkaido prefecture (Destination 1) as an example, the parameter is the highest at 0.64, indicating that choice of this destination is influenced most strongly by

Table 7.3 Model estimation results: nested logit model

–	Tourism participation		Destination choice		Travel mode choice							
–					Air		Shinkansen		Railway		Bus	
–	Parameter		Parameter		Parameter		Parameter		Parameter		Parameter	
Constant term												
January	−6.28	*	–	–	−1.18	*	−0.95	*	−1.39	*	−1.77	*
February	−6.30	*	–	–	−1.39	*	−1.36	*	−1.66	*	−1.81	*
March	−4.97	*	–	–	−1.49	*	−0.83	*	−1.72	*	−3.36	*
April	−5.07	*	–	–	−1.73	*	−1.01	*	−1.42	*	−2.48	*
May	−4.78	*	–	–	−1.85	*	−1.22	*	−1.83	*	−2.61	*
June	−6.58	*	–	–	−1.23	*	−0.88	*	−0.97	*	−1.89	*
July	−6.04	*	–	–	−1.48	*	−0.87	*	−1.41	*	−2.33	*
August	−5.17	*	–	–	−1.49	*	−1.14	*	−1.33	*	−2.59	*
September	−5.93	*	–	–	−1.26	*	−0.80	*	−0.93	*	−3.38	*
October	−4.90	*	–	–	−2.04	*	−1.06	*	−2.24	*	−2.75	*
November	−6.61	*	–	–	−1.43	*	−0.87	*	−0.55	–	−2.19	*
December	−6.42	*	–	–	−1.31	*	−0.74	*	−0.83	*	−2.61	*
Explanatory variable for tourism participation												
Age	−2.55	*	–	–	–	–	–	–	–	–	–	–
Married	0.29	*	–	–	–	–	–	–	–	–	–	–
Education	0.09	+	–	–	–	–	–	–	–	–	–	–
Household	−0.08	+	–	–	–	–	–	–	–	–	–	–
Income	0.01	+	–	–	–	–	–	–	–	–	–	–
Car	0.18	+	–	–	–	–	–	–	–	–	–	–
Holiday	0.19	*	–	–	–	–	–	–	–	–	–	–
Explanatory variable for destination choice												
Tourist arrival			0.02	*	–	–	–	–	–	–	–	–
Festival			0.07	+	–	–	–	–	–	–	–	–
Household size × distance			−0.01	+	–	–	–	–	–	–	–	–
Nature motivation × density of natural park			3.86	*	–	–	–	–	–	–	–	–
Culture motivation × density of culture facilities			0.28	*	–	–	–	–	–	–	–	–
Shopping motivation × density of stores			1.38	*	–	–	–	–	–	–	–	–
Sport motivation × density of sport facilities			12.3	*	–	–	–	–	–	–	–	–
Explanatory variable for travel mode choice												
Age			–	–	0.89	*	0.29	–	−0.48	–	3.51	*
Travel with others			–	–	−0.75	*	−1.02	*	−0.12	–	−0.55	+
Travel time			–	–	−1.63 *							
Travel fee			–	–	−0.54 +							

(continued)

Table 7.3 (continued)

–	Tourism participation		Destination choice		Travel mode choice							
–					Air		Shinkansen		Railway		Bus	
–	Parameter		Parameter		Parameter		Parameter		Parameter		Parameter	
Inclusive value parameters												
Participation	0.71	*(*)	–	–	–	–	–	–	–	–	–	–
Destination1	–	–	0.64	*( )	–	–	–	–	–	–	–	–
Destination2	–	–	0.31	(*)	–	–	–	–	–	–	–	–
Destination3	–	–	0.25	*(*)	–	–	–	–	–	–	–	–
Destination4	–	–	0.33	*(*)	–	–	–	–	–	–	–	–
Destination5	–	–	0.01	+(*)	–	–	–	–	–	–	–	–
Destination6	–	–	0.01	+(*)	–	–	–	–	–	–	–	–
Destination7	–	–	0.04	+(*)	–	–	–	–	–	–	–	–
Destination8	–	–	0.01	+(*)	–	–	–	–	–	–	–	–
Destination9	–	–	0.43	*(*)	–	–	–	–	–	–	–	–
Destination10	–	–	0.30	*(*)	–	–	–	–	–	–	–	–
Destination11	–	–	0.09	*(*)	–	–	–	–	–	–	–	–
Destination12	–	–	0.11	*(*)	–	–	–	–	–	–	–	–
Destination13	–	–	0.12	*(*)	–	–	–	–	–	–	–	–
Destination14	–	–	0.13	*(*)	–	–	–	–	–	–	–	–
Destination15	–	–	0.16	*(*)	–	–	–	–	–	–	–	–
Destination16	–	–	0.37	*(*)	–	–	–	–	–	–	–	–
Destination17	–	–	0.30	*(*)	–	–	–	–	–	–	–	–
Destination18	–	–	0.62	*(+)	–	–	–	–	–	–	–	–
State dependence												
Participation	−0.39	*	–	–	–	–	–	–	–	–	–	–
Destination	–	–	0.24	*	–	–	–	–	–	–	–	–
Travel mode	–	–	3.56(car)*		1.47	*	3.83	*	3.70	+	9.62	+
Initial log-likelihood							−22926.3					
Converged log-likelihood							−8136.19					
McFadden's Rho-squared							0.64					
Sample size							1,253					

Inside the parenthesis: null hypothesis "parameter=1"; Outside the parenthesis: null hypothesis "parameter=0"

+ significant at the 90 % level; * significant at the 95 % level

travel mode choice. Travel mode choice conditioned on this destination shows weaker substitution. In other words, the change in the utility of an alternative travel mode in this destination nest could dramatically change the probability of the destination being chosen. Weaker substitution suggests that tourists tend to use a certain mode when they travel to this destination. As explained previously, Hokkaido prefecture is separated from the rest of Japan, so it is difficult for tourists to reach it by surface modes. However, for some destinations, such as 5, 6, 7 and 8, the inclusive value parameters are rather small, suggesting that the choices of these destinations are less influenced by travel mode choice, or that travel mode choice conditioned on these destinations shows higher substitution. This may be because the transport systems in these regions are well developed, and it is therefore convenient for tourists to use any of the five travel modes to reach them.

The result that tourist destination choice is influenced by travel mode choice is consistent with previous research. Fukuda and Morichi's (2002) study also confirmed the interrelations between these two choice aspects. They developed a modeling framework for recreational travel behavior that incorporated the interrelations between destination and travel mode choices using a bivariate dichotomous probit model. However, their model can only be used to analyze binary choice behavior, while a NL model can incorporate multiple-choice alternatives and at the same time can represent the relation between various aspects of choice.

3. Influential Factors
This section discusses the influences of explanatory variables.

(a) Tourism participation: It can be seen that the parameters of marital status, education level, income and car ownership are positive and statistically significant at the 95 % level, while the parameters of age and household size are negative. This may be because married people have a partner to travel with, and a person with a higher education level may have more interest in tourism, may have better access to information and may possess greater knowledge of tourism. A higher income level can eliminate monetary constraints on participation in tourism, and car ownership makes travel more convenient. The negative parameter for household size implies that individuals from larger households may face financial constraints and family commitments, so they are less likely to participate in tourism. From the value of the constant term, we can see that if other variables are the same, individuals are more likely to travel in March, April, May, August, September and October and less likely to travel in January, February, June, July, November and December.

(b) Destination choice: It is found that tourists are more likely to visit destinations with more tourist arrivals, which can be explained by the effects of social interaction. In other words, tourists may find destinations visited by more people more attractive. In addition, the number of festivals has been proved to have a significant influence on destination choice. The parameter for the interaction term of household size and distance is negative, which implies that tourists from larger households are more likely to choose destinations that are closer to their residential area. This may be to reduce the overall travel cost, and group decisions may be easier if they choose closer destinations.

In the existing research, it has been argued that motivation for tourism has an important impact on destination choice. In this survey, respondents were asked about their motivation to travel, including motivations for nature activities, cultural activities, shopping and sport activities. This study examines the influence of motivation by incorporating it as an interaction term with certain destination characteristics. The results show that tourists with motivation for nature activities are more likely to choose destinations with larger areas devoted to nature parks. Tourists motivated by cultural activities are more likely to choose destinations with more cultural facilities. Tourists with the motivation of shopping are more likely to choose destinations with more department stores, while those with sporting motivations are more likely to choose destinations with more sports facilities. Density of sport facilities is especially influential, which indicates that increasing the number of sports facilities will significantly increase the number of tourists motivated by sports.

(c) Travel mode choice: The results show that travel time and cost have negative influences on travel mode choice. The value of time implied by this model is $-1.64 / -0.53 = 3{,}020$ Yen per hour (for comparison, the average salary of national public servants is about 2,000 Yen per hour). To estimate the influences of age and travel with others, it is necessary to fix the parameters of these two variables to zero for one alternative. In this study, private car is chosen as the base alternative. One can see that older tourists are more likely to choose aircraft or bus travel. This result is intuitive, because older people may find it exhausting to drive a long distance. Regarding the influence of travel companions, it is confirmed that those who travel with others are more likely to use private cars, potentially to reduce the overall travel cost or because cars can provide a private space in which to communicate.

The constant terms reflect the inherent preference for travel mode (car is chosen as the base mode). The negative parameters for all public transportation modes indicate that tourists have a preference for car travel if other variables are equal. This preference is especially strong in certain months, such as May and October. This may be caused by unobserved factors. To promote the use of public transportation modes, it is essential to understand these unobserved factors.

7.4.1.5 Policy Implications of Modeling Analysis

These results have important policy implications. Research into tourism participation behavior offers one means of assessing the latent demand for tourism, which is essential for both tourism forecasting and policy making. In Japan, the question of how to encourage people to make full use of their free time to participate in tourism activities, especially domestic tourism, has recently become an important political issue. The Japanese government has proposed various policies to encourage people to participate in tourism. This study provides a tool for evaluating the effectiveness of these policies. An additional policy implication is that the study addresses environmental issues resulting from the temporal imbalance of tourism demand. Specifically, the result indicates that length of national holiday has a significant influence on decisions to participate in tourism. Based on this result, having region-specific Golden Weeks (where the Golden Week holiday falls at different times according to region) will certainly eliminate the concentration of tourism demand.

Destination management is of concern because there is an imbalance in visits to regional domestic tourist destinations. It is increasingly important to encourage tourists to visit local attractions. Especially in recent years, the rural areas of Japan have suffered from depopulation. The development of a tourism industry in these rural areas will support those who have suffered from depopulation. Some strategies of destination management can be derived from this study. For example, a prefecture can market its tourism destinations by targeting larger families in nearby regions; some prefectures (e.g., Hokkaido, Yamanashi, Shizuoka and Okinawa) could increase their numbers of tourist arrivals dramatically by improving their transportation services.

Furthermore, policy implications of promoting public transport modes can be drawn from this study. Because travel mode choices conditioned on some destinations (e.g., Chiba, Tokyo, Kanagawa, Toyama, Ishikawa, and Fukui) show higher substitution, the use of public transport modes to these destinations will increase significantly if the service levels of public modes increase.

The analysis also offers a tool for forecasting future tourist behavior. Because the population in Japan is aging, tourism patterns are expected to change accordingly. In addition, the demographic change may also change motivations for tourism, which will further influence tourist behavior. Improved understanding of such changes will provide insights into policy decisions.

7.4.2 Case Study 2: Analysis of Tourists' Time Allocation in Multiple Activities

It is expected that tourists will participate in many kinds of activities during trips to satisfy various needs. Temporal constraints force tourists to decide how to make effective use of limited time during travel. Therefore, tourists need to decide which activities to participate in and how long to spend on each activity. Considering tourists' joint decision-making process concerning their participation in activities and time allocation, this study adopts Bhat's (2008) multiple discrete–continuous extreme value (MDCEV) model.

7.4.2.1 Multiple Discrete-Continuous Extreme Value Model

When traveling, a tourist under a time constraint may decide to participate in several activities. The tourist needs to decide which activities to participate in and how much of his/her limited time to allocate to each activity. For such a decision, it is expected that the tourist will allocate his/her time so that the total utility derived from all the activities is maximized. In this sense, the utility-maximizing principle can be applied. Let there be K different activities to which a tourist can allocate time. Let t_k be the time spent on activity k $(k=1, 2, \ldots, K)$. Utility is specified based on the utility structure proposed by Bhat (2008) and defined as the sum of the utilities obtained from allocating time to each activity:

$$U_n = \sum_{k=1}^{K} \gamma_k \psi_{nk} ln(\frac{t_{nk}}{\gamma_k} + 1) \tag{7.12}$$

$$\psi_{nk} = exp(\beta z_{nk} + \varepsilon_k) \tag{7.13}$$

where

U_n : the total utility to tourist n of allocating time to all K activities,
ψ_{nk} : the marginal utility of tourism activity k when tourist n allocates 0 time to it,
t_{nk} : the time that tourist n allocates to activity k,
γ_k : a satiation parameter,
z_{nk} : a set of attributes characterizing activity k performed by tourist n, and
ε_k : an error term, assumed to follow a standard extreme value distribution.

Then, the marginal utility of time allocation in activity k can be computed as:

$$\frac{\partial U_{nk}}{\partial t_{nk}} = \Psi_{nk} / (\frac{t_{nk}}{\gamma_k} + 1). \tag{7.14}$$

From Eq. (7.14), we can see that $\boldsymbol{\Psi}_{nk}$ is the marginal utility of activity k when time allocation is 0, which is explained by a set of attributes characterizing activity k and tourist n. As time allocation t_{nk} increases, the marginal utility will decrease. This diminishing marginal utility reflects tourists' satiation when the duration of one activity increases. The parameter γ_k is introduced to influence this kind of satiation. A larger value of γ_k indicates the lower diminishing rate of marginal utility, which means that tourists are less likely to be satiated with activity k and to be willing to spend more time on it. Tourists may have different levels of satiation with different activities, which can be represented by the parameter γ_k.

Tourist n is assumed to maximize random utility U_n subject to the time constraint $\sum_{k=1}^{K} t_k = T$, where T is total time. Then the Lagrangian function can be defined to solve the optimal time allocation:

$$L = \sum_k \gamma_k \, exp(\beta z_{nk} + \varepsilon_k) \mathrm{In}(\frac{t_{nk}}{\gamma_k} + 1) - \lambda(\sum_{k=1}^{K} t_k - T) \tag{7.15}$$

where λ is the Lagrangian multiplier associated with the time constraint. The Kuhn–Tucker first-order conditions for the optimal time allocations are given below.

$$\begin{aligned} & exp(\beta z_{nk} + \varepsilon_k) / (\frac{t_{nk}}{\gamma_k} + 1) - \lambda = 0, \quad if \ t_{nk} > 0 \\ & exp(\beta z_{nk} + \varepsilon_k) / (\frac{t_{nk}}{\gamma_k} + 1) - \lambda < 0, \quad if \ t_{nk} = 0 \end{aligned} \tag{7.16}$$

When tourist n participates in activity k, $t_{nk} > 0$; otherwise, $t_{nk} = 0$. This represents discrete choice (i.e., whether to participate in activity k). Because the tourist should participate in at least one of the K activities, let activity 1 be one to which a tourist allocates a nonzero amount of time. The Kuhn–Tucker condition can be written as:

$$\lambda = exp(\beta z_{n1} + \varepsilon_1) / (\frac{t_{nk}}{\gamma_k} + 1). \tag{7.17}$$

Substituting Eq. (7.17) into Eq. (7.16) and taking logarithms, the Kuhn–Tucker condition can be rewritten as:

$$\begin{aligned} V_k + \varepsilon_k &= V_1 + \varepsilon_1, \quad if\ t_{nk} > 0\ (k = 2,3,\ldots,K) \\ V_k + \varepsilon_k &< V_1 + \varepsilon_1, \quad if\ t_{nk} = 0\ (k = 2,3,\ldots,K) \end{aligned} \tag{7.18}$$

where, $V_k = \beta z_{nk} - ln(\frac{t_{nk}}{\gamma_k} + 1)\ (k = 1,2,3,\ldots,K)$.

We specify a standard extreme value distribution for ε_k and assume that ε_k is independent of t_k and independently distributed across alternatives. The probability that a tourist participates in M instances of the K activities given ε_1 can be calculated based on the study of Bhat (2008):

$$P(t_2, t_3, \ldots, t_M, 0, 0, \ldots, 0) = [\prod_{k=1}^{M} (\frac{1}{t_k + \gamma_k})][\sum_{k=1}^{M} (t_k + \gamma_k)][\frac{\prod_{k=1}^{M} e^{V_k}}{(\sum_{k=1}^{K} e^{V_k})^M}](M-1)!. \tag{7.19}$$

Therefore, the log-likelihood function of the model is:

$$LogL_n = \sum_n \ln\{[\prod_{k=1}^{M} (\frac{1}{t_k + \gamma_k})][\sum_{k=1}^{M} (t_k + \gamma_k)][\frac{\prod_{k=1}^{M} e^{V_k}}{(\sum_{k=1}^{K} e^{V_k})^M}](M-1)!\}. \tag{7.20}$$

To estimate Eq. (7.20), the maximum likelihood estimation method is applied. The MDCEV model has a simple and elegant closed form that is easy to estimate.

7.4.2.2 A Tourist Time Use Survey

The data used in this study were collected from a tourist time use survey in the prefecture of Tottori in 2007 based on a face-to-face interview. Tottori is best known for its sand dunes, which are a popular tourist attraction, drawing visitors from outside the prefecture. The interview survey was conducted over four seasons in 1 year at 16 major tourism destinations in Tottori. As a result, 761 valid responses were obtained, including data on individual characteristics and travel-related attributes. Individual characteristics included gender, age, occupation, and residential location, while travel-related attributes included destination, travel party, travel mode, departure time, duration of stay and expenditure. The survey included very detailed information on each tourist attraction visited, from which we obtained information about

Table 7.4 Explanatory variables: MDCEV model

Explanatory variables	Description
Individual attributes	
Age	Age of the tourist
Employment status (dummy variable)	1: employed, 0: otherwise
Residential area (dummy variable)	1: living in Tottori Prefecture, 0: otherwise
Travel experience (dummy variable)	1: visited Tottori Prefecture before, 0: otherwise
Travel related attributes	
Travel mode (dummy variable)	1: private car, 0: otherwise
Travel party (dummy variable)	1: travel alone, 0: otherwise
Travel season (dummy variable)	1: winter, 0: otherwise

Table 7.5 Model estimation results: MDCEV model

Explanatory variables	Nature	Hot spring		Culture		Heritage		Shopping		Sport		Amuse	
Constant term	–	–1.79	*	–1.18	*	–2.53	*	–0.34	–	–5.18	*	–2.12	*
Age	–	0.14	*	0.12	*	0.21	*	–0.01	–	0.04	–	–0.05	–
Employment status	–	0.08	–	0.01	–	0.28	–	–0.04	–	0.86	*	–0.24	+
Residential area	–	0.12	–	1.16	*	0.51	*	1.24	*	1.83	*	1.38	*
Travel experience	–	0.22	–	–0.15	–	0.04	–	0.86	*	1.38	*	0.23	–
Travel mode	–	0.19	–	–0.17	+	–0.18	*	–0.03	–	0.99	*	0.76	*
Travel party	–	–0.06	*	–0.05	*	0.01	–	–0.01	–	–0.24	*	–0.06	–
Travel season	–	0.89	*	0.55	*	0.15	–	0.69	*	0.88	*	–0.08	–
γ_k	65.0 *	141	*	85.4	*	66.3	*	30.4	*	204	*	83.5	*

+ significant at the 90 % level; * significant at the 95 % level

the activities in which that tourist participated. In this study, the activities are divided into seven categories: nature (e.g., sand dunes), hot springs, culture (e.g., museums), heritage, shopping, sport and amusement. It was observed that 75 % of the tourists participated in more than one activity during their trips.

7.4.2.3 Factors and Variations in Activity Preference

By excluding missing values of explanatory variables, a final sample of 612 responses was used in this study. The model is estimated by the maximum likelihood estimation method using R statistical software. To estimate the model, it is necessary to fix all the parameters to zero for one alternative. In this study, activity 1 (visit natural attractions) is chosen as the base alternative; all the parameters for activity 1 are fixed at zero. Explanatory variables for the developed model are shown in Table 7.4 and estimation results are presented in Table 7.5. The log-likelihood value at convergence of the final MDCEV model is –7027. The corresponding value for the MDCEV model with only the constants in the baseline preference terms is

−7125. The likelihood ratio test for testing the presence of exogenous variable effects is 196, which is substantially larger than the critical chi-square value (63.69) with 42 degrees of freedom at the 99 % significance level.

The parameters of age are significant at the 95 % level for activities involving hot springs, culture or heritage. The positive parameters indicate that as age increases, the baseline preference of these three activities also increases. The effects of employment status indicate that employees have a higher baseline preference for sporting activities, while they have a lower baseline preference for amusement activities. The parameters of residential area suggest that tourists residing outside Tottori Prefecture have a lower baseline preference for all activities, especially for sporting activities. The results for travel experience indicate that travel experience has a significant effect on shopping and sporting activities. Tourists who have visited Tottori Prefecture previously have a higher baseline preference for these two activities. The effects of travel mode indicate that tourists who traveled by private car have a higher baseline preference for sporting and amusement activities but have a lower baseline preference for culture and heritage. The effects of travel party indicate that tourists who traveled alone have a lower baseline preference for hot springs, culture and sporting activities. This indicates that tourists are more likely to participate in these activities with others. The parameters of travel season show that the baseline preferences for hot springs, culture, shopping and sport are higher in the winter season. The main sporting activity for tourists in Tottori is skiing, so it is reasonable that tourists are more willing to participate in sport in winter.

The satiation parameter γ_k is significant for all activities at the 95 % level. The results indicate the high level of satiation for shopping and the low level of satiation for sport and hot spring activities. This is consistent with the observation that for shopping, the participation rate is high but the average duration is short, while for sport, the participation rate is low, but if the tourist participates in sport, the duration is quite long. This variation in satiation levels for activities cannot be reflected without the parameter γ_k.

7.4.2.4 Implications for Sustainable Tourism

Enjoying tourism activities is an important factor in quality of life for many people, and it is therefore important for public policy makers, including transport policy makers, to support such activities. On the other hand, improving the quality of time use during travel could contribute to enhancing tourists' travel satisfaction and consequently the improvement of life satisfaction.

The findings of this study provide some insights into tourists' time-use behavior. Some implications for tourism management can be drawn from the results. Tourists' behavior patterns are an important issue for tourism destination management. Specifically, the kinds of activities in which tourists participate, how long they spend on each activity and the factors that influence behavior can provide information on the management of tourism infrastructure (e.g., how many pieces of infrastructure need to be constructed/improved, or the business hours for tourism attractions). This information may contribute to the promotion of tourism and thereby increase revenue. Moreover, the study offers a tool to forecast demand for attractions when the current situation changes. In addition, because tourist activities have varying degrees of impact on the environment, forecasts of tourists' time allocation could provide a tool for estimating overall environmental impact resulting from tourism activities. Policies for sustainable tourism development could be proposed accordingly. For example, an environmental tax on tourism could be introduced based on the analysis of tourist energy consumption (e.g., consumption of transport, food, water, or accommodation) and pollutant emissions derived from their activities.

7.5 Conclusion

A successful tourism policy relies heavily on policy makers' understanding of tourist behavior and the incorporation of this knowledge into the decision-making process. Tourists' travel decisions usually involve a number of interrelated choices made over time and across space under various constraints, including choices of destination, composition of the travel party, dates of departure, choices of accommodation and travel modes, travel routes, activities, and time and money expenditure. To obtain a better understanding of tourist behavior, it is necessary to deal with all the relevant choice aspects of tourist behavior in an integrated way.

The chapter provides two integrated behavior models that can be used to evaluate the effects of policies to achieve sustainable tourism development. The first model jointly represents three interrelated tourist choices: whether to travel (i.e., tourism participation), destination, and travel mode. The model is based on a nested logit model with three levels: tourism participation choice, destination choice and travel mode choice. Choices regarding tourism participation and destination are indispensable for exploring economic sustainability and social equity. Travel mode choice, together with the other two parts, provides information necessary for calculating environmental loads from tourism activities. On the other hand, the second model considers tourists' time use involving multiple activities by using an MDCEV model. Such time-use behavior analyses are required for evaluating economic and environmental sustainability because time use is closely linked with spending at destinations. Information on type of activity and length of time is necessary to calculate the environmental loads of tourism activities. The most important feature of the above two models is that the behavioral interdependences are explicitly incorporated into the modeling process. This feature allows policy makers to evaluate comprehensively the heterogeneous effects of a specific tourism policy on various aspects of tourists' choice decisions as well as the synergic and/or canceling out effects of a combination of policies in a consistent way. Furthermore, it is also possible to predict changes in tourist behavior that occur because of changes in travel style and socioeconomic situations, and to explore the kinds of policies that could effectively support the sustainable growth of tourism demand.

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Chapter 8
Taxation Policies for Promoting Fuel-Efficient Vehicle Ownership and Use

Masashi Kuwano, Akimasa Fujiwara, Junyi Zhang, and Makoto Tsukai

Abstract This study evaluates the effects of taxation policies on promoting fuel-efficient vehicle ownership and use. Ownership is described as choice of vehicle type based on a paired combination logit (PCL) model and use is represented by a copula-based multivariate survival (CMS) model that includes both holding duration and annual distance traveled. To estimate the integrated model, the PCL model is first estimated and then incorporated into the CMS model. Policy effects are evaluated by calculating changes in CO_2 emissions under different taxation policies. An empirical analysis was conducted of data from a questionnaire survey in the Chugoku region of Japan in 2006. Through the simulation analysis of vehicle-related taxes, it is found that increasing the fuel tax is the most effective means of reducing CO_2 emissions, followed by the auto tax and weight tax collected at vehicle inspections. Moreover, it is further observed that, contrary to our expectation, increasing the acquisition tax actually leads to an increase in CO_2 emissions.

Keywords Copula • Integrated model • Taxation policy • Vehicle ownership and use

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8.1 Passenger Car Policies and Existing Studies of Behavior Models

The transport sector accounts for more than 20 % of total global emissions (Nurul Amin 2009). Although reducing emissions from the transport sector requires a reduction in vehicle ownership, this is more difficult than it appears because there is no competitive alternative travel mode that can replace private vehicles and meet people's higher-order mobility needs. Probably because of the inconvenient service by other travel modes in many countries, including developed countries, vehicle ownership, especially of gasoline-powered vehicles, increases every year. Under the current growing trend, gasoline-powered vehicles are likely to remain the dominant form of mobility in the global market, especially in developing countries in the next 20 or 30 years. Therefore, it seems more realistic for policy makers to encourage people without sufficient support from public transportation systems to own and use more fuel-efficient vehicles instead of simply discouraging vehicle ownership and consequently making policies socially unacceptable.

Generally, policies concerning vehicle ownership and use can be grouped into four categories: enforcing regulations and institutional rules, pricing, technological development, and enlightenment. The success of enforcement is usually determined by the effectiveness of regulations and rules as well as the compliance of consumers. Innovative technological developments such as electric, plug-in hybrid or other low-emission vehicles could ultimately be one of the means of reducing emissions. The success of technological development requires seamless support from the other three categories of policies. Enlightened policy relies heavily on people's voluntary cooperation, and success requires stakeholders to make enormous and continuous efforts to communicate with people, making cost effectiveness questionable. Compared with the other three policy categories, pricing is expected to play the most critical role in reducing emissions from vehicles, although this method is old-fashioned and usually involves difficult consensus building. Better pricing schemes should be proposed.

From the public policy-making perspective, taxation is the most relevant pricing tool. In most countries, new vehicle taxation systems have been introduced to reduce environmental loads from passenger vehicles. Household vehicle ownership consists of the three stages of "vehicle purchase," "vehicle use," and "duration of vehicle ownership" (de Jong 1996). Previous studies have attempted to describe complicated vehicle ownership behavior (Best and Lanzendorf 2005). For example, Bhat and Sen (2006) applied discrete–continuous models to describe choices of vehicle type and the use of vehicles, simultaneously. However, there have been no studies to incorporate the correlation between the stages of vehicle use and holding duration (i.e., duration of vehicle ownership). Recently, a rapid increase in fuel prices has caused an overall decrease in vehicle use and a shift to vehicles with more fuel-efficient engines. There is no doubt that change in the running costs of private vehicles affects choices of vehicle type, vehicle use, and holding duration. To reduce total emissions from passenger vehicles, promoting the ownership of low-emission vehicles, and reducing frequency of vehicle use and trip distance are important. Vehicle ownership behavior is affected by household and individual attributes as well as policy variables such as tax, service levels of transit systems and land use. When changing vehicle-related taxation, policy makers should take note of differences in those taxes collected at different stages. For example, vehicle purchasers in Japan must pay an acquisition tax, a consumption tax and an annual holding tax (i.e., auto tax) in addition to the weight tax at vehicle inspection every 2 years while they own the vehicle. Obviously, vehicle users also need to pay fuel taxes. If the above four types of taxes were paid at different stages, it may be expected that their influence on household vehicle ownership and use behavior would change. For more effective tax policies, vehicle ownership and use behavior should be integrated by explicitly incorporating their interdependence.

On this basis, this study evaluates the effects of taxation policies on the promotion of fuel-efficient vehicle ownership and use by developing an integrated model. The model simultaneously considers vehicle purchase, vehicle use, and duration of vehicle ownership by accommodating the correlations between these three aspects of vehicle use. To develop the integrated model, we first formulate a vehicle type choice model based on a paired combination logit (PCL) model. Then, in terms of the stages of vehicle use and duration of vehicle ownership, we build a further copula-based multivariate survival (CMS) model of annual traveling distance and holding duration, and finally combine the CMS and PCL models. A copula is a function that allows us to combine prespecified (univariate) marginal distributions to obtain a (multivariate) joint distribution with the help of a limited number of dependence parameters in a flexible way and at a low computational cost (Nelsen 2006). Of particular note is that the copula function is flexible to represent the correlated random variables that may follow different marginal distributions.

8.2 The Japanese Automobile Tax System

Taxes on passenger cars include an acquisition tax, an auto tax and a light car tax (collected by local governments), and a weight tax (collected by central government). These taxes are briefly summarized below. In addition, there is a fuel tax.

Acquisition Tax

When a car is purchased, an acquisition tax is charged. The tax rate is 5 % for passenger cars, except for light cars, and 3 % for other types.

Auto Tax

The auto tax is a kind of property tax charged for the possession of a car. Auto tax for a passenger car with an engine capacity of less than 1,000 cc is 29,500 yen/year. For passenger cars with an engine capacity of less than 3,000 cc, an extra tax of 5,000 yen per 500 cc must be paid. If the displacement is larger than 3,000 cc, the tax rises sharply, and the amount reaches 111,000 yen/year for a car with an engine capacity of more than 6,000 cc.

Light Car Tax
This tax is a kind of priority tax that is charged for the possession of a light car (with engine displacement of 550 cc or less). The tax rate is 7,200 yen/year for a light passenger car, and 4,000 yen/year for a light truck. One can see that there is a large gap between the auto tax and the light car tax.

Weight Tax
The weight tax is collected to fund the construction of road infrastructure. This tax is included as a source of general revenue for the central government. The tax rate is 6,300 yen/year for each half tonne. It is paid at the time of vehicle inspection (usually every 2 years).

8.3 Model of Vehicle Ownership and Use

8.3.1 *Modeling Framework*

In this study, we develop an integrated model simultaneously including "vehicle purchase," "vehicle use," and "duration of vehicle ownership." The stage of "vehicle purchase" consists of two choices: (1) number of vehicles, and (2) vehicle type. However, the private vehicle market is already saturated in Japan. Therefore, there has been no significant increase in number of vehicles over recent decades, because households already own a sufficient number of vehicles. Therefore, this study only models vehicle type choice in the vehicle purchase stage and applies a disaggregate choice model to describe choice behavior.

Vehicle use and the duration of vehicle ownership can be decomposed into decisions such as the purpose of vehicle use, destination choice, travel mode choice, and timing. However, no action related to vehicle use and duration of vehicle ownership can be modeled without detailed data, but these models are beyond the scope of this study. This study focuses on annual traveling distance and holding duration, and applies the survival model to analyze these. Although the survival model is not behaviorially-oriented, it can appropriately describe the probability density of these continuous variables, and the model frame can be flexibly designed. The remaining subsections discuss the characteristics of the models at each stage of vehicle ownership and use.

8.3.2 *Vehicle Type Choice Modeling*

Disaggregate choice models are generally used to describe the choice of vehicle type. Household characteristics and vehicle attributes are used as explanatory variables (Adler et al. 2003; Potoglou and Kanaroglou 2007). Moreover, it is expected that vehicle use preference significantly influences choice of vehicle type. And, the detailed individual characteristics of factors such as vehicle purpose and frequency are not modeled in this study. Therefore, these unobserved factors of vehicle use are considered to be latent characteristics in our model. Therefore, we introduce annual traveling distance in the previous year as a proxy variable for vehicle use preference.

From the perspective of modeling vehicle type choice, it is recognized that the unobserved correlations between the alternatives should be considered, in case ignoring the correlations leads to biased estimates (Brownstone et al. 2000). This study applies the Paired Combination Logit (PCL) model to represent the correlations. The PCL model was proposed by Chu (1989), and Koppelman and Wen (2000) studied the theoretical aspects in terms of the model structure, properties, and estimation. The model allows correlation between any pair of alternatives. Joint partial dependence among the alternatives is added as similarity coefficients $\sigma_{jj'} \in (0,1)$ where the alternatives j and j' are identical if $\sigma_{jj'}$ takes a value of 1, while the alternatives j and j' are independent if $\sigma_{jj'}$ takes a value of 0.

The choice probability is described as follows:

$$P(j) = \frac{\sum_{j \neq j'} \left(1-\sigma_{jj'}\right) \left\{ exp\left(\frac{V_j}{1-\sigma_{jj'}}\right) + exp\left(\frac{V_{j'}}{1-\sigma_{jj'}}\right) \right\}^{-\sigma_{jj'}} exp\left(\frac{V_j}{1-\sigma_{jj'}}\right)}{\sum_{q=1}^{n-1} \sum_{r=q+1}^{n} \left(1-\sigma_{qr}\right) \left\{ exp\left(\frac{V_q}{1-\sigma_{qr}}\right) + exp\left(\frac{V_r}{1-\sigma_{qr}}\right) \right\}^{1-\sigma_{qr}}} \tag{8.1}$$
$$= \sum_{j \neq j'} P(jj')P(j \mid (jj')$$

where $\sigma_{jj'}$ is the similarity coefficient between alternatives j and j', V_j is the nonstochastic term of the utility for alternative j, $P(jj')$ is the marginal probability of the alternative pair j and j', and $P(j \mid (jj')$ is the conditional probability of choosing alternative j given that the alternative pair jj' has been chosen.

8.3.3 *Joint Modeling of Holding Duration and Annual Traveling Distance*

Survival analysis has been extensively used to model the probability density function (PDF) of a continuous variable before the event that it concerns. In the area of transportation, there are studies applying it to the analysis of duration of a vehicle holding (Hensher 1985; Gilbert 1992), the duration of activities (Mannering and Hamed 1990), and the length of time between vehicle accidents (Mannering et al. 1994). In this study, vehicle annual traveling distance (d) and vehicle holding duration (t) are examined using survival models.

The annual traveling distance is usually influenced by a number of factors. In this study, we introduce household attributes, main-user attributes, and vehicle attributes as the covariates in our model. These covariates are also used in the model of vehicle holding duration. In addition, the logsum variable estimated in the vehicle type choice models is introduced as a covariate, because it can be an index of the price and quality of vehicles available in the current market. The coefficient of the vehicle type logsum would be negative, because the higher the expected utility of vehicle choice alternatives, the shorter the duration of vehicle holding.

In 2009, a rapid increase in fuel price caused a decrease in vehicle kilometers traveled and an increase of vehicle replacement with smaller ones. There is no doubt that the change in vehicle running cost affects both vehicle use and holding duration. In other words, annual travel distance and holding duration are dependent. This study proposes a Copula-based Multivariate Survival (CMS) model to capture the interdependence between these two factors. In the next section, we first formulate a univariate survival model to analyze annual traveling distance and vehicle holding duration, and we then develop a multivariate survival model with copula functions.

8.3.3.1 A Univariate Survival Model

In a survival model, time T is considered to be a continuous random variable. It measures the time elapsed before an event occurs. In this study, it is used to represent the duration of ownership of a vehicle and annual traveling distance. Suppose that T has a continuous PDF $f(t)$, where t is a sample of T. The distribution function ($F(t)$) shows the probability that the failure time is less than or equal to t:

$$F(t) = \int_0^t h(s)ds = Pr[T \leq t]. \tag{8.2}$$

Then the hazard function can be written as a function of the distribution function ($F(t)$) and the corresponding density function ($f(t)$) of the random variable t:

$$h(t) = \frac{f(t)}{1 - F(t)}. \tag{8.3}$$

Another important construct in hazard-based models is the survival function ($S(t)$), which gives the probability of duration t before the focal event occurs. This is related to the distribution function as follows:

$$S(t) = Pr(T \geq t) = 1 - Pr(T \leq t) = 1 - F(t). \tag{8.4}$$

Because $f(t) = -dS(t)/dt$, the hazard can also be written as:

$$h(t) = -\frac{d(\ln S(t))}{dt}. \tag{8.5}$$

If the hazard is known, the survival function can be found through:

$$S(t) = exp(-\int_0^t h(u)du). \tag{8.6}$$

Then, the density function of t is expressed by:

$$f(t) = h(t)exp(-\int_0^t h(t)dt). \tag{8.7}$$

As shown in Eqs. (8.2)–(8.7), $f(t)$, $S(t)$ and $h(t)$ are mathematically identical. If the distribution $f(t)$ is known, then $S(t)$ and $h(t)$ can be uniquely derived. A number of PDFs for $f(t)$ have been proposed and examined in previous studies. This study examines three PDFs for the vehicle holding duration model; these are: (1) Weibull, (2) log-logistic, and (3) log-normal.

In our model, some covariates may change over time. For example, household characteristics could change before a vehicle is replaced. Pendyala et al. (1995) showed that the relationship between vehicle ownership and income is not constant. In such a case, to incorporate the changes of the covariate into the model, time-varying covariates should be introduced. Let the interval "0 to t" be divided into N nonoverlapping intervals, $t_0 < t_1 < \ldots < t_N$, where $t_0 = 0$ and $t_N = t$. The covariates are assumed to be invariant within each interval, but they may vary from one interval to another. The survival function is rewritten as follows:

$$S(t) = exp(-\int_0^t h(t \mid X(t))du) \tag{8.8}$$

where $X(t)$ denotes a time-varying covariate at time t. The time-varying covariates are modeled as a step function, with different values through several intervals between $t = 0$ and $t = t_N$:

$$X(t) = \begin{cases} X_0 & t_0 < t <= t_1 \\ X_1 & t_1 < t <= t_2 \\ X_2 & t_2 < t <= t_3 \\ . & \\ . & \\ X_N & t_{N-1} < t <= t_N \end{cases} \tag{8.9}$$

The survival function with the time-varying covariate $X(t)$ is expressed as follows:

$$S(t \mid X(t)) = \prod_{n=1}^{N} \frac{S(t_n \mid X_{n-1})}{S(t_n \mid X_n)} \times S(t \mid X_N). \tag{8.10}$$

In this study, the vehicle holding duration model is constructed using survey data on household vehicle ownership from 1996 to 2006. The exact holding durations of previous cars purchased and disposed of from 1996 to 2006 were observed. When a vehicle is observed at the start and end of a holding period, there is no problem. However, if the vehicle was bought before the survey, the sample cannot be used because we do not have the characteristics of the household and main user before 1996. Furthermore, if the vehicle is in use during the survey period, the exact holding duration cannot be observed. It is already known that estimating a model without these censored observations leads to self-selection bias (1995). Therefore, in this study, we incorporate left- and right-censored periods to avoid selection bias. The following log-likelihood function for the survival function model incorporates the censoring observation:

$$L = \prod_{i \in NC} f(t \mid X(t)) \cdot \prod_{i \in RC} S(t \mid X(t)) \cdot \prod_{i \in LC} \frac{f(t \mid X(t))}{S(v \mid X(t))} \cdot \prod_{i \in LRC} \frac{S(t \mid X(t))}{S(v \mid X(t))} \tag{8.11}$$

where *NC*, *RC*, *LC*, and *LRC* are the numbers of noncensored, right-censored, left-censored, and left-and-right-censored observations, respectively.

8.3.3.2 Copula-Based Multivariate Survival Models

A bidimensional copula is a function $C_\theta : [0,1]^2 \to [0,1]$ with the following properties:

1. $C_\theta(0,u) = C_\theta(u,0) = 0$ and $C_\theta(1,u) = C_\theta(u,1) = u$, for all $u \in [0,1]$, and
2. $C_\theta(\bullet,\bullet)$ is bi-increasing; that is, for all $u' > u$ and $v' > v$:

$$C_\theta(u',v') - C_\theta(u',v) \geq C_\theta(u,v') - C_\theta(u,v)$$

Let *T* and *D* be two random variables with $F^T(t)$, $F^D(d)$ as marginal distribution functions, and let C_θ be a bidimensional copula. Then the function $C_\theta(F^T(t), F^D(d))$ is a cumulative distribution function. Thus, copula functions are used to redefine joint distributions using the given margins. For any pair of scalar random variables (*T*, *D*) with distribution function *F*, there exists a copula function C_θ such that:

$$F(t,d) = C_\theta[F^T(t), F^D(d)]. \tag{8.12}$$

The copula function C_θ is unique if the marginal distribution functions $F^T(t)$, $F^D(d)$ are continuous. Here, θ is a dependence parameter, which simultaneously characterizes the dependence between $F^T(t)$ and $F^D(d)$.

One can also define copula densities in the same way as one defines probability densities. Let the distribution of (T, D) be continuous. The differentiated form of Sklar's theorem splits the joint density of *T* and *D*, $f(t,d)$, into the product of marginal densities $f^T(t)$ and $f^D(d)$, and the copula density, $c_\theta(u,v) \equiv \partial^2 C_\theta(u,v) / \partial u \partial v$, becomes:

$$f(t,d) = f^T(t) f^D(d) c_\theta[F^T(t), F^D(d)]. \tag{8.13}$$

Because $F^T(t)$ and $F^D(d)$ have uniform distributions, $c_\theta(u,v)$ is the density of $(F^T(t), F^D(d))$ at (u,v) and is also the conditional density of $F^D(d)$ at point v given $F^t(T) = u$.

To estimate unknown parameters, the following log-likelihood function is adopted:

$$ln\ L(\alpha,\beta,\theta) = ln\ f^T(t;\alpha) + ln\ f^D(d;\beta) + ln(c_\theta[F^T(t;\alpha), F^D(d;\beta);\theta]). \tag{8.14}$$

Copulas themselves can be generated in different ways, including the method of inversion, the geometric method, and the algebraic method. A rich set of copula functions have been generated using these methods. In this paper, we consider one of the simplest forms of these copulas: the Archimedean copulas, which are useful for bivariate data. Archimedean copulas have been widely used because of their mathematical tractability. The Archimedean class is rich, and as a result, it does not seem to be very restrictive. A detailed description of copula models is given by Nelsen (2006). From the Archimedean class, we will consider the Gumbel, Clayton, and Frank copulas, which present several desired properties, and select the best copula based on the goodness-of-fit index.

In this paper, copula-based models are used to capture and explore the dependence relations between vehicle holding duration and annual traveling distance. For a pair (T, D) (T: vehicle holding duration; D: annual traveling distance) with a joint distribution function F, the joint survival function is given by $S(t,d) = P[T > t, D > d]$. The margins of S are the functions $S(t,-\infty)$ and $S(-\infty,d)$, which are the univariate survival functions $S^T(t)$ and $S^D(d)$, respectively.

Let X and Y be continuous random variables with copula C_{TD}. Let α and β both be strictly decreasing on Ran T and Ran D, respectively. Then:

$$C_{\alpha(T)\beta(D)}(u,v) = u + v - 1 + C_{TD}(1-u, 1-v). \tag{8.15}$$

Using Eq. (8.15) and the copula function (8.12), the joint survival function $S(t,d)$ is given as follows:

$$\begin{aligned} S(t,d) &= 1 - F^T(t) - F^D(d) + F(t,d) \\ &= S^T(t) + S^D(d) - 1 + C_\theta(F^T(t), F^D(d)) \\ &= S^T(t) + S^D(d) - 1 + C_\theta(1 - S^T(t), 1 - S^D(d)) \\ &= \hat{C}\,(S^T(t), S^D(d)) \end{aligned} \tag{8.16}$$

where function $\hat{C}_\theta$ is the survival copula of T and D.

8.4 Revealed Preference Survey

Data used in this study were obtained from a revealed preference survey of household vehicle ownership and use behavior. The data were collected in October 2006 from households living in the Chugoku area of Japan. All the householders were asked to answer questions about their households and individual attributes, and the attributes of passenger vehicles owned in the past 11 years (i.e., from 1996 to 2006). As a result, questionnaires from 500 households with vehicles were collected. The sample used in this study includes 757 vehicles, among which 372 (49.1 % of the sample) were replaced or disposed of between 1996 and 2006, and 101 (13.3 % of the sample) were purchased before 1996 (left-censored data). The remaining 284 vehicles (37.5 % of the sample) were purchased after 1996 but were still used by households at the time of survey (right-censored data).

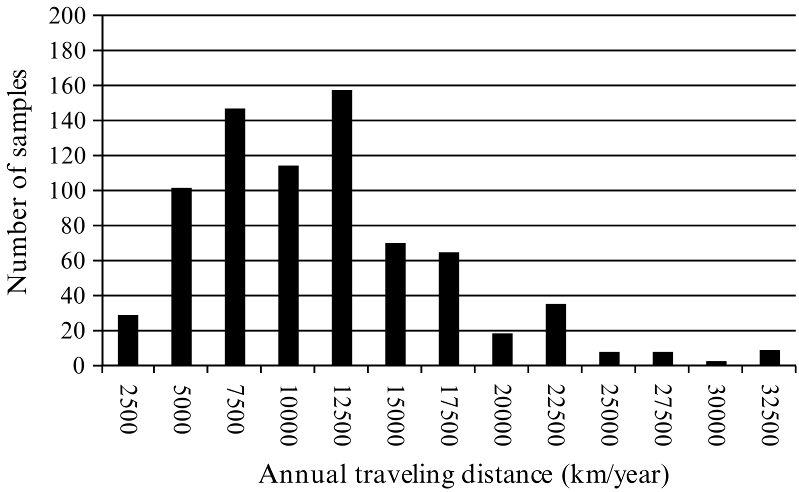

Fig. 8.1 Distribution of annual vehicle traveling distance

In Japan, vehicle type is usually classified based on engine displacement. This classification is well known to vehicle users. Because tax systems vary according to engine displacement, vehicle users in Japan are very sensitive to this when purchasing vehicles. Therefore, this study defines the alternatives to passenger vehicles based on engine displacement, considering that this category is directly related to evaluation of fuel consumption, emissions and effects of vehicle taxes. Exploring the choice behavior of passenger vehicle types is important for both marketers and public policy makers, especially considering that an increasing number of people are expressing concern about environmental issues. For the purposes of estimating the choice models presented in this paper, the following three choice alternatives are adopted.

- Small vehicles: passenger vehicles with engine displacement smaller than or equal to 660 cc
- Medium-sized vehicles: passenger vehicles with engine displacement greater than 660 cc and smaller than or equal to 2,000 cc
- Large vehicles: passenger vehicles with engine displacement greater than 2,000 cc

In the sample, medium-sized vehicles comprise the majority of vehicle types (54.7 %), and the shares of small and large vehicles are 27.3 % and 18.0 %, respectively.

Figure 8.1 shows the annual vehicle traveling distance, calculated from vehicle holding duration and total traveling distance. The average distance traveled is 10,015 km/year. Figure 8.2 shows the vehicle holding duration for those replaced or disposed of from 1996 to 2006. The average vehicle holding duration was 4.48 years.

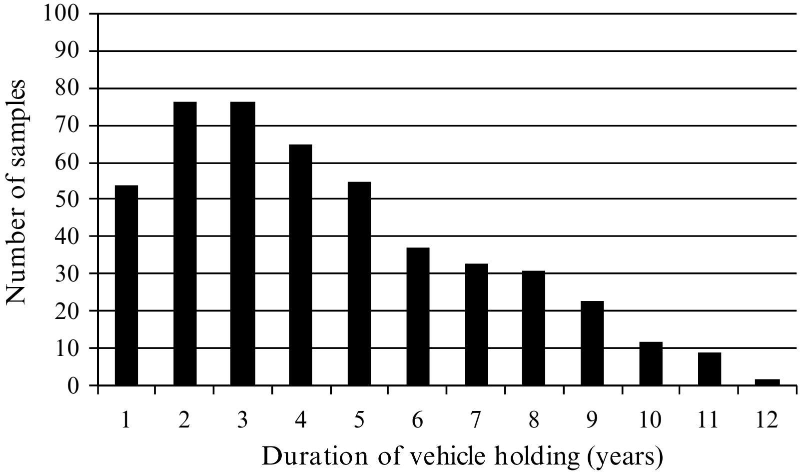

Fig. 8.2 Distribution of vehicle holding duration

8.5 Analysis of Model Estimation Results

8.5.1 Vehicle Ownership: Vehicle Type Choice

Estimation results for the vehicle type choice model are shown in Table 8.1. The adjusted McFadden's Rho-squared is 0.236, suggesting that the model is an acceptable representation of household vehicle type choice in this study. Although fuel efficiency of the vehicle and taxes are used as explanatory variables in previous studies, this study does not consider them because the alternatives are defined according to engine displacement, which is strongly related to these variables.

Concerning the influence of household attributes, the coefficient of the average age of husband and wife has a positive sign and is statistically significant. This implies that older people prefer to own larger vehicles. For vehicle attributes, the composite variable "price/household income" and number of passenger seats have negative values and are statistically significant. These mean that inexpensive and smaller vehicles are preferred. The coefficient of annual traveling distance in the previous year has a positive sign and is statistically significant, which means that households traveling large distances prefer to have medium-sized or large vehicles.

For dependence among the alternatives, the similarity coefficient between medium-sized and large vehicles is statistically significant, but the others are not. These results indicate an unobserved correlation between medium-sized and large vehicles, and the PCL model is validated. One of the supposed reasons for the correlation between medium-sized and large vehicles is the difference in tax systems. The taxes on passenger vehicles include an acquisition tax, an auto tax, a light car tax, a weight tax, and a fuel tax. These tax systems are divided into two main classes:

Table 8.1 Estimation results: vehicle type choice model

Explanatory variable	Parameter	*t*-score
Household attributes		
Average age of husband and wife (M,L)[a]	0.018*	1.70
Number of workers (M,L)	−0.175	−0.57
Number of household members (M,L)[a]	−0.116	−0.99
Number of household children (M,L)v	0.216	1.62
Vehicle attributes		
Price/household income (S,M,L)[a]	−2.377**	−2.29
Number of passenger seats (S,M,L)[a]	−0.361*	−1.90
Vehicle use attributes		
Annual traveling distance in the last year (M,L)[a]	0.687**	4.50
Constant term		
Constant term (M)[a]	−0.346	−0.65
Constant term (L)[a]	−0.800	−1.42
Similarity parameters		
θ_{12}	0.0001	−0.10[b]
θ_{13}	0.452	−0.47[b]
θ_{23}	0.066*	−2.29[b]
Sample size	757	
Goodness-of-fit indices		
Initial log-likelihood	−831.650	
Converged log-likelihood	−631.973	
McFadden's rho-squared	0.240	
Number of parameters	12	
Adjusted McFadden's rho-squared	0.236	

Note: *: significant at the 10 % level; **: significant at the 1 % level

[a]Capitals in parentheses indicate the alternatives associated with this variable: (S)~660cc, (M) 661~2000cc, (L) 2001cc~

[b]Similarity parameters are defined as $\sigma_{jj'} = exp(\phi_{jj'})/(1+exp(\phi_{jj'}))$ during estimation. The t-score shown in this Table is for $\phi_{jj'}$

(1) tax systems for light vehicles, and (2) tax systems for medium-sized and large vehicles. As can be seen in Sect. 8.2, there is a large gap between the tax systems for medium-sized and large vehicles and that for light vehicles.

8.5.2 Vehicle Use: Annual Traveling Distance and Holding Duration

8.5.2.1 Selection of Baseline Hazard

In this section, we compare several candidates for underlying baseline hazard to discover which best predicts annual traveling distance and holding duration based on the Bayesian Information Criterion (BIC) value. We examined three

Table 8.2 Goodness-of-fit indices for different baseline hazards

	Converged log-likelihood	Number of coefficients	BIC
Annual traveling distance			
Weibull distribution	–548.014	13	591.105
Log-normal distribution	–539.727	13	582.818
Log-logistic distribution	–539.170	13	582.261
Holding duration			
Weibull distribution	–897.835	16	875.437
Log-normal distribution	–918.031	16	904.501
Log-logistic distribution	–929.054	16	912.963

BIC $= -\ln(L_C) + 0.5p\ln(N)$; $\ln(L_C)$ is the log-likelihood vale at convergence; p is the number of coefficients; N is the number of samples

Table 8.3 Comparison of copula functions

Coupla type	Converged log-likelihood	Number of coefficients	BIC
Normal copula	−1314.282	30	1413.722
Gumbel copula	−1361.425	30	1460.865
Clayton copula	−1313.370	30	1412.810
Frank copula	−1316.284	30	1415.724
Without copula	−1361.570	29	1457.698

distributions: (1) Weibull, (2) log-normal, and (3) log-logistic distributions with respect to annual traveling distance and holding duration. The candidate models are estimated for each dependent variable. Table 8.2 shows the baseline hazards for annual traveling distance and holding duration. It is clear that the log-logistic distribution provides the best goodness of fit. The hazard model of holding duration with a Weibull distribution has the highest model accuracy. Therefore, this study adopts the log-logistic distribution of baseline hazard of annual traveling distance, and the Weibull distribution for that of holding duration.

8.5.2.2 Selection of Copula Function

Having selected the baseline hazards, we examined which type of copula was the most suitable for capturing the interdependence between annual traveling distance and vehicle holding duration. Here, four copulas were considered candidates: (1) normal, (2) Gumbel, (3) Clayton, and (4) Frank. Table 8.3 reports the BIC values for the CMS models. Comparison of the BIC values indicates that the CMS model with a Clayton copula provides the best goodness of fit. Moreover, fit of the CMS model with a Clayton copula is better than that of the conventional model assuming no interdependence between annual traveling distance and vehicle holding duration. Thus, the proposed CMS model outperforms the conventional model.

8.5.2.3 Analysis of Model Estimation Results

The estimation results of the CMS model with the Clayton copula, which has the highest goodness-of-fit index, are shown in Table 8.4. The coefficient of copula is statistically significant and has a negative sign, which indicates negative interdependence between annual traveling distance and holding duration. Therefore, the holding duration decreases as the annual traveling distance increases.

The estimated coefficients related to annual traveling distance, and all the coefficient estimates for household attributes, main-user attributes, and vehicle attributes have the expected signs. The coefficients of distances to the nearest railway station and supermarket have positive signs and are significant. These results seem reasonable because households with low accessibility to stations and supermarkets tend to depend on vehicle mobility. Moreover, vehicles mainly used for commuting tend to travel greater distances annually because the coefficient of commuting distance has a positive sign and is significant. The coefficient of the wife dummy is negative, indicating that wives drive shorter distances than other respondents. The signs of the coefficients for medium-sized and large vehicles indicate that they drive longer distances than do small vehicles. The coefficient of running cost, which is a policy variable, has a negative sign and is significant. This result indicates that annual vehicle kilometers traveled decreases as fuel tax and gasoline price increase.

Observing the estimation results related to holding duration, we find that all coefficient estimates have the expected signs. The coefficient of number of household vehicles has a positive sign and is statistically significant, implying that a household with multiple vehicles holds each vehicle for a longer period. The negative coefficient of income suggests that households with high incomes tend to replace their vehicles much earlier than others. With regard to the coefficients of main-user attributes, that of the commuting vehicle dummy indicates that vehicles used for commuting are held for shorter periods than other vehicles. The coefficient of main-user age has a significant and positive value. Older main users tend to hold their vehicles for longer periods. The coefficient of the logsum variable, which is calculated according to the vehicle type choice model, has a significantly negative sign. The logsum variable is a measure of the price and quality of vehicle available on the market. The negative impact of logsum variable on duration indicates that holding duration decreases as the expected utility of an alternative to the vehicle increases. Therefore, an attractive vehicle alternative would shorten the holding duration.

8.6 Differentiated Effects of Taxation Policies: A Simulation Analysis

Using the estimated models, we simulate scenarios of possible policy measures. The simulations yield the number of replacements, changes in vehicle share, expected annual traveling distance, and amount of CO_2 emissions under the different scenarios. First, the "business as usual (BAU)" scenario describes a situation without a policy (Case 0: BAU). The other scenarios with policies are as follows.

Table 8.4 Estimation results of vehicle use model: CMS model

Covariates	Parameter	*t*-score
Interdependency between holding duration and annual traveling distance		
Type of copula function	*Clayton*	
Copula parameter	–0.081**	–39.5
Annual traveling distance		
Type of distribution	*log-logistic*	
Gamma	2.943**	52.63
Constant	2.537**	6.33
Household attributes		
Distance to the nearest rail station (m)	1.938**	2.54
Distance to the nearest supermarket (m)	5.604**	2.23
Household income	–0.019	–1.46
Main-user attributes		
Commuting distance to office (km)	2.133**	2.40
Employed statement of main-user	0.010	0.12
Age of main-user	3.06.E-04	0.10
Housewife dummy	–0.380**	–2.47
Vehicle attributes		
Middle-sized vehicle	0.516**	5.15
Large-sized vehicle	0.785**	5.37
Holding cost[a]	–0.027**	–3.32
Running cost	–0.013**	–2.53
Holding duration		
Type of distribution	*Weibull*	
Gamma	2.502**	23.21
Constant	0.026**	2.45
Household attributes		
Distance to the nearest rail station (m)	0.950	0.53
Distance to the nearest supermarket (m)	5.176	1.25
Number of workers	–0.002	–0.02
Number of license holders[a]	0.090	0.56
Number of household vehicles[a]	1.155**	8.98
Household income	–0.160**	–5.83
Main-user attributes		
Commuting vehicle	–0.612**	–4.49
Age of main-user[a]	0.028**	3.20
Vehicle attributes		
Holding cost[a]	–0.089**	–4.47
Running cost[a]	–0.047**	–2.31
Middle-sized vehicle	0.357*	1.86
Large-sized vehicle	0.524*	1.84
Vehicle age	–0.258**	–5.78
Expected utility		
Logsum value from vehicle type choice[a]	–0.986**	–5.90
Sample size	757	
Goodness-of-fit indices		
Initial log-likelihood[b]	−1482.219	
Converged log-likelihood	−1313.365	

Note: *: significant at the 10 % level; **: significant at the 1 % level

[a]Time-varying covariate

[b]Log-likelihood with all coefficients to 0, except Gamma and constant

Case 1: A 10 % increase in running costs from 117 to 129 Japanese yen per liter of gasoline.

Case 2: An increase in the holding cost. The increase in holding costs HC_j for vehicle type j are calculated by Eq. (8.17):

$$HC_j = (129 - 117) \times MVKM / FE_j \tag{8.17}$$

where $MVKM$ indicates mean annual traveling distance (i.e., 10,015 km/year), and FE_j stands for the mean fuel efficiency of vehicle type j.

Case 3: An increase in the purchase costs. The cost is adjusted to be identical to that in Case 1. The increase in purchase costs PC_j for vehicle type j are calculated by Eq. (8.18):

$$PC_j = (129 - 117) \times MVKM \times MHD / FE_j \tag{8.18}$$

where MHD represents mean holding duration (i.e., 4.48 years).

The variables related to household and main-user attributes are assumed to remain unchanged, except the age of the main user. Moreover, we assumed that the dependence structure between annual traveling distance and holding duration remains unchanged (i.e., the copula parameter is fixed).

For the simulations, we first calculate the logsum value from the vehicle type choice model, which gives the attractiveness of vehicles available on the market. Second, the joint model of annual traveling distance and holding duration is estimated using this logsum value, and the expected annual traveling distance and survival probability of holding duration for each sample are calculated. For the households predicted to replace their vehicles (i.e., mean survival probability in the holding duration is less than 0.5), the vehicle type choice model is used to calculate the probability of replacement. These probabilities are summarized and combined with those of households that do not replace their vehicles, and the distribution of vehicle type share is calculated. Third, the mean fuel efficiency of the whole sample is estimated using the distribution of vehicle type share. Finally, the CO_2 emissions are calculated by multiplying the mean fuel efficiency by the mean annual distance traveled.

The simulation results are shown in Table 8.5. The results are summarized in terms of relative change to the BAU scenario (Case 0). These results therefore predict the impacts of the respective policy measures only. The first row of Table 8.5 shows that an increase in running costs leads to a decrease in annual traveling distance, which seems logical. However, the rate of decrease in annual traveling distance is only 2.5 %. Increasing running costs influences holding duration in two ways. First, running cost has a direct negative impact on the duration of vehicle holding. Second, increases in running cost decrease traveling distance, which increases vehicle holding duration because these variables have negative interdependence. The direct effect dominates the indirect effect as shown in Table 8.5. Holding durations also decrease with an increase in running cost, and more vehicles are replaced by increasing running cost. This is attributed to the fact that the data in this study were collected in rural areas. Compared with large metropolitan areas,

Table 8.5 Simulation results (relative change to the BAU scenario (Case 0))

	Scenarios		
	Case1	Case2	Case3
Comparison item	Increase of running cost	Increase of holding cost	Increase of purchase cost
1. Number of vehicle replacements	+11.88 %	+25.25 %	−01.98 %
2. Share of small-sized vehicle	+02.22 %	+03.11 %	+00.00 %
3. Share of middle-sized vehicle	+00.00 %	+00.73 %	−00.24 %
4. Share of large-sized vehicle	−04.10 %	−08.20 %	+00.82 %
5. Expected annual traveling distance	−02.50 %	−01.38 %	−00.04 %
6. Expected holding duration	−05.47 %	−11.03 %	+01.46 %
7. Total CO_2 emissions	−02.80 %	−01.95 %	+00.03 %

people's mobility in rural areas depends greatly on private vehicles because of the lower level of public transportation services, and it is consequently difficult to reduce annual traveling distance. Therefore, the rate of decrease in the annual traveling distance is small, but the frequency of purchasing new vehicles with high fuel efficiency increases. In case 2, with increased holding cost, the annual traveling distance is decreased, and the number of replacements is increased. The simulation results are similar to those of case 1. Moreover, from the comparison between cases 1 and 2, the change in share of vehicles is caused by changes in the vehicle replacement rate. If the vehicle replacement rate is increased, the number of smaller vehicles is increased. Focusing on the results of case 3, we find that the annual traveling distance and vehicle share are not significantly changed.

From the perspective of environmental impact, increases in running cost have a considerable impact on reduction of CO_2 emissions, followed by holding cost. However, increase in purchase cost contributes to a slight increase in CO_2 emissions. This result indicates that the tax on vehicle use (i.e., an increase in fuel tax) is the most effective way to reduce CO_2 emissions.

8.7 Conclusions

Calculations of fuel consumption and the resulting CO_2 emissions from passenger vehicles need to take into account how cars are purchased and used. Accordingly, policies to reduce fuel consumption and CO_2 emissions should be evaluated in a way that properly reflects buyers' and users' decisions. There are various interdependences related to decisions on household vehicle ownership and use. Classifying these decisions into the three aspects of choice of vehicle type, annual traveling distance, and holding duration, this study first developed an integrated model of these aspects in combination. Annual traveling distance and holding duration are jointly modeled based on a CMS model. In addition, a PCL model was adopted to represent vehicle type choice, and the expected maximum utility of vehicle type choices from the PCL model is introduced into the CMS model to describe the dependence of annual traveling distance and holding duration on choice of vehicle type. As a case study, questionnaire survey data on household vehicle ownership and use behavior between 1996 and 2006 were collected in the Chugoku region of Japan in 2006 and used to confirm the effectiveness of the integrated model. In this study, four common copula functions were compared empirically. As a result, the Clayton copula was found to be most suitable for the marginal function to describe both annual traveling distance and holding duration. The proposed CMS model with a Clayton copula is superior to the conventional model without considering interdependence between the two aspects of vehicle ownership. The estimated coefficients showed that annual traveling distance and holding duration are significantly correlated. It is also found that holding duration decreases as annual traveling distance increases because of the negative interdependence between the two variables. Moreover, the coefficient of the logsum variable in the vehicle holding duration was negative and significant. The negative impact on the vehicle holding duration indicates that it decreases as the expected utility in vehicle replacement increases.

Using the proposed model, a simulation analysis was conducted to examine the effects of vehicle-related taxes on household vehicle ownership and use as well as CO_2 emissions. It was observed that taxation in the vehicle use stage has the strongest influence on reduction of CO_2 emissions, and an increase in tax in that stage can significantly encourage people to purchase a vehicle with smaller engine displacement. It is difficult to prevent people purchasing vehicles because of their door-to-door convenience and private space, so taxation policies can balance people's mobility needs and the negative impacts of using cars. Furthermore, increases in running costs tend not only to reduce annual traveling distance but also to increase the frequency of replacement of vehicles with those of smaller engine displacement. The frequent turnover of smaller vehicles may also be influenced by car users' variety-seeking behavior and/or adaptation to changes of life stage. Fortunately, it is expected that such a shift will lead to a reduction of CO_2 emissions from the improved energy efficiency of newly replaced vehicles.

From the above analysis, taxation policies could encourage people to own and use smaller vehicles, which usually have better energy efficiency than other types of vehicles. Under the influence of improved energy efficiency, however, there may be an energy rebound effect that decreases the expected energy saving or conversely increases energy consumption (i.e., the efficiency measures may backfire) (Greening et al. 2000; Sorrell et al. 2007; Vera and Denise 2009). Because analysis of such rebound effects is beyond the scope of this study, refer to Yu et al. (2013) in this book for a detailed discussion of rebound effects. Recently, in the area of CO_2 emissions, carbon emission-differentiated vehicle taxes and carbon taxes as instruments of internalization have attracted increasing attention (OECD 2009; Giblin and McNabola 2009). Carbon taxes are charged directly based on the amount of carbon emissions during use, whereas carbon-differentiated vehicle taxes are charged when a vehicle is purchased. Carbon taxes are intended to reduce carbon emissions directly, and carbon-differentiated vehicle taxes are an attempt to influence vehicle ownership rather than use. To reduce CO_2 emissions from passenger vehicles, other effective measures should be taken in combination depending on the local context. CO_2 emissions can also be reduced by other strategies, such as enforcing regulations and institutional rules (e.g., setting standards for CO_2 emissions), technological development (e.g., EV/PHEV, ITS), and education (e.g., motivating travel behavior change by providing travel-related and non-travel-related information as well as effective incentives). From a much broader perspective, technological development could include the transformation of urban structures (e.g., compact cities, transit-oriented urban structures, polycentric urban structures, and walkable and bikable cities) and the introduction of comprehensive transportation networks with better connectivity and accessibility. All these measures are expected to influence vehicle ownership and use behavior in different ways and are worth examination in future. To examine the effects of the above measures comprehensively, changes in behavior should be clarified systematically, and behavior models should be further improved by reflecting the decision-making mechanisms in the behaviors concerned.

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Chapter 9
Integrated Analysis of Household Energy Consumption Behavior Across the Residential and Transport Sectors

Biying Yu, Junyi Zhang, and Akimasa Fujiwara

Abstract Given the rapid increase of energy demand in the world, especially in Asia, reducing energy use has been widely acknowledged as a means for both meeting future energy needs and addressing environmental problems (GHG emissions and climate change). This chapter aims to present an energy policy analysis that can answer the question of how to reduce household energy consumption from a behavioral perspective. Residential and transport energy consumption behavior in a household may be expected to be correlated, because of the existence of the rebound and self-selection effects. To examine this expectation, a mixed MDCEV and MNL-MDCEV models are first introduced into the energy field, from which the necessity for joint representation of residential and transport energy consumption is confirmed. Under this integrated framework, land-use policy is taken as an example and is designed to reduce energy use by explicitly controlling self-selection effects. This chapter on the one hand questions the traditional sector-oriented policy scheme by emphasizing the importance of cross-sector policy, while on the other hand it gauges the effect of land-use policies and shows the effectiveness of soft policy on household energy saving.

Keywords Household energy consumption behavior • Joint representation • Land-use policy • Self-selection effects

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9.1 Energy Consumption Trend in Asia and Household Behavior

According to World Energy Outlook (2009), energy consumption accounts for 65 % of the world's greenhouse gas (GHG) emissions. By 2030, under the Reference Scenario, which assumes no change in government policies, world primary energy demand will be a dramatic 40 % higher than in 2007. The unsustainability of current energy trends and the urgent need for action to realize a low-carbon society have been internationally recognized. It is also revealed that non-OECD countries account for over 90 % of the increase; their share of global primary energy demand rises from 52 % to 63 %. China and India represent over 53 % of incremental demand to 2030. Coupled with strong growth from ASEAN, it is becoming increasingly important to reduce energy use in Asia. Although, energy consumption per capita is much lower in developing countries than in industrialized countries (e.g., in the ESCAP region, the average per capita energy consumption was only 604 kg of oil equivalent (kgoe) and that of developing countries was 333 kgoe, compared with the world average of 1,692 kgoe), household energy consumption is expected to increase throughout the Asian and Pacific regions together with economic growth and rising per capita income. Consequently it is important to analyze household energy consumption patterns to formulate policies for the promotion of sustainable energy consumption (ESCAP 2009).

To date, the main tools used to ameliorate the energy problem are technological development (e.g., the improvement of end-use efficiency, the introduction of new types of energy, and housing insulation and ventilation) and economic control measures (e.g., fuel price, tax, subsidies, and discounts). Many countries have devoted substantial public resources to research and development of energy-efficient technologies, which are likely to take several decades for diffusion. Energy efficiency, however, depends on both these technologies and the choices of users (Allcott and Mullainathan 2010). Even if people choose to use advanced technologies, there is still another problem that the energy rebound effect may arise, cutting the expected energy savings or increasing energy consumption (i.e., backfire effects) (Greening et al. 2000; Sorrell 2007; Vera and Denise 2009). As for economic control measures, with increasing income, it is expected that monetary incentives will gradually lose their luster. Consequently, there is significant concern that for at least the next few decades, these tools will not be sufficient to address climate change and energy security issues (Armel 2008). Furthermore, such concerns are particularly severe among some developing countries, like China and India, because they are enjoying rapid economic development and facing a challenging goal for CO_2 reductions in the near future. In this context, some researchers emphasize the role of the behavioral sciences in dealing with the energy problem (Allcott and Mullainathan 2010), especially the problem of household energy consumption (i.e., including both residential and vehicle energy consumption), which has historically been difficult to address using traditional economic methods (Yu et al. 2011). Note that household energy consumption is defined here as actual direct energy used for domestic end uses and for personal transport over 1 year, while indirect energy embedded in goods and services purchased by households is excluded.

Although previous research on residential energy consumption or travel behavior has received a great deal of interest, integrated analyses of energy consumption across both the residential and transport sectors do not gain the same level of attention from either academics or practitioners. This is probably because of the widely adopted sector-oriented policy decision scheme. Because of the trade-offs between the residential and transport energy use caused by limited resources (e.g., time and money) and the self-selection effects caused by subjective factors (e.g., motivation, preference, and attitude), these two sectors are not independent of each other (Yu et al. 2011, 2012). In other words, any behavioral change may alter the whole household energy consumption pattern (including both residential and transport sectors). Therefore, in a low-carbon future, both residential and transport energy consumption deserve to be emphasized.

This chapter aims to analyze energy policy to answer the question of how to reduce household energy consumption in both the residential and transport sectors from a behavioral perspective. Before the policy analysis, a preliminary analysis is first conducted. Traditionally, residential energy consumption and travel behavior have been treated as separate. However, because of the existence of rebound effects and the self-selection effect, it is expected that residential energy consumption and travel may be correlated. With this taken into consideration, this study first constructs a new type of energy consumption model based on the mixed Multiple Discrete–Continuous Extreme Value (MDCEV) modeling framework to examine the necessity for joint representation of residential and transport energy consumption. Building upon this foundation, the effect of land-use policy is further examined, incorporating self-selection effects and the monetary trade-offs between end users in the developed mixed Multinomial Logit-MDCEV (MNL–MDCEV) model.

The remainder of this chapter is organized as follows. The next section introduces the motivations of the integrated household energy consumption behavior analysis. Section 9.3 is the premise for the later policy analysis, which examines the necessity for joint representation of residential and transport energy consumption behavior. Section 9.4 presents an example of energy policy development (i.e., land-use policy). This chapter concludes in Sect. 9.5 with a discussion of future research and policy issues.

9.2 Motivations for the Joint Representation of Residential and Transport Energy Consumption

Household energy is consumed by users of appliances at home and of vehicles to support participation in various activities that play an important role in meeting various household and individual needs. Because ownership and use of home appliances and vehicles reduces disposable household income, residential and transport energy consumption may be interrelated, suggesting that any behavioral change

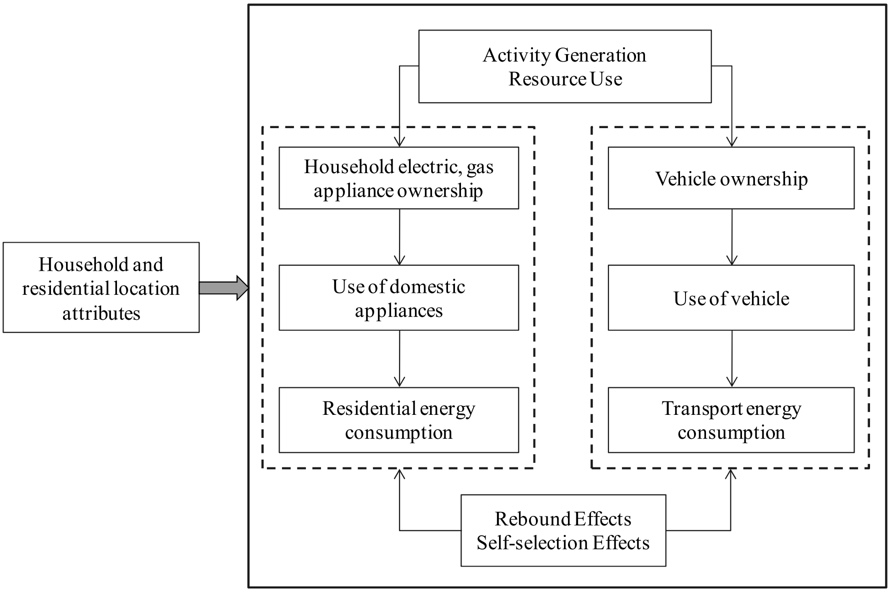

Fig. 9.1 Energy related behavior components

alters energy consumption patterns. Such interrelationships may be observed with respect to ownership and/or use of various appliances (e.g., refrigerators, air-conditioners and washing machines) and vehicles (e.g., passenger cars and motorcycles), implying that multidimensional modeling approaches are required. A joint representation of these interrelationships also has important applications for revealing rebound effects (Vera and Denise 2009). For example, these days, energy-saving technologies have been actively developed. However, the introduction of energy-saving technology does not mean that household energy consumption will be automatically reduced. One concern is that households may become insensitive to their energy consumption behavior, and as a result, total energy consumption may even increase; that is, rebound effects may occur. Because energy-saving technologies for different appliances and vehicles have not developed equally and households may differ in their preferences for these new technologies, the sources of the rebound effects may vary across appliances and vehicles as well as households. The above concerns motivate us to develop an integrated model to cover both residential and transport energy consumption (see Fig. 9.1).

Another important issue related to household energy consumption is the self-selection effect. In statistics, self-selection arises in any situation in which individuals select themselves into a group. In the context of fully considering objective factors, the self-selection effect is expected from unique subjective household characteristics that could affect an individual's behavior, such as motivational factors, environmental awareness, and special tastes in driving and lifestyle (Cao 2009). For example, individuals with high environmental self-consciousness are motivated to care about the environment and to reject energy-intensive practices. In other words, such people are more likely to save energy in fulfilling their activities and to use it more efficiently or to participate in non-energy-consuming activities such as jogging in a park instead of running on a treadmill and commuting by bicycle instead of by car. Other people who have a specific preference for driving may prefer to live in a suburban area and to depend on a car for their lifestyle. As may be seen, the self-selection effect is an inherent trait of some groups of people and may affect all individual behavior, which includes both residential energy consumption and travel behavior.

With the possible existence of rebound effects and self-selection effects, it seems plausible that the joint representation of household energy consumption behavior across residential and transport sectors is more consistent with real behavioral mechanisms. This chapter identifies the necessity and rationality of integrated analysis by considering the issue of rebound effects caused by the money and self-selection effects in the energy realm.

9.3 Joint Modeling of Household Energy Consumption Behavior in Residential and Transport Sectors

Given the above concerns, this section aims to explore the necessity for joint representation of energy consumption behavior, which refers to ownership and use of appliances and vehicles in residences and for transport. For this purpose, a mixed MDCEV model proposed by Bhat (2005, 2008) is applied here.

9.3.1 The Mixed MDCEV Model

The mixed MDCEV uses a utility-maximizing resource allocation modeling framework in which household income is apportioned to several categories (including savings). The model describes the households' expenditure on different types of end uses and services that satisfy households' needs and desires. Unlike the traditional discrete–continuous models explained previously, the mixed MDCEV model can include choices of multiple alternatives simultaneously. In addition, it can implicitly incorporate the monetary rebound and self-selection effects.

Assume that there are K different end uses (including saving) to which a household can allocate its money. Let x_k be the consumption quantity of end use $k(k=1,2,\cdots,K)$. The utility that a household derives from energy consumption is specified as the sum of the utilities obtained from spending money on each end use, as shown below:

$$U(x)=\sum_{k=1}^{K}\frac{\gamma_k}{\alpha_k}[exp\left(\beta' z_k+\varepsilon_k\right)]\left\{(\frac{\gamma_k}{\alpha_k}+1)^{\alpha_k}-1\right\} \tag{9.1}$$

Here, $U(x)$ is the total utility derived from allocating a nonnegative amount of the total budget to the consumption (or expenditure) of each end use (or alternative) *k*, including savings. With the above utility function, it is assumed that a household maximizes its utility subject to its budget constraint of $\sum_{k=1}^{K} e_k = E$, where *E* is the total budget (e.g., expenditure, disposable income, or available time). As a result, the linear competitive relationship among end uses is reflected in the model. Note that only one type of budget constraint can be represented—in this study, a monetary budget constraint. In fact, using the monetary budget constraint can at least partially represent the influence of a time budget because time allocated to activities increases the energy that households consume. φ_k is the baseline utility for money spent on end use *k*, and the α_k and γ_k parameters are introduced next.

The parameter α_k represents a satiation parameter that expresses diminishing marginal utility with increasing consumption of end use *k*. Depending on the value of α_k, various types of nonlinear relationships among various end uses can be accommodated. When $\alpha_k = 1$ for all *k*, this indicates the absence of a satiation effect (i.e., the marginal utility becomes constant); it also illustrates that the competitive relation between end use *k* and other end uses is linear. As α_k deceases from the value of 1, the satiation effect for alternative *k* increases. When $\alpha_k \rightarrow 0$, the utility function for end use *k* collapses to $U_k = \gamma_k \varphi_k ln(x_k / \gamma_k + 1)$, suggesting the existence of a log-linear relationship. α_k can also take a negative value, and when $\alpha_k \rightarrow -\infty$, this implies immediate and full satiation (i.e., infinite decrease in the marginal utility).

The parameter γ_k ($\gamma_k > 0$) is a translation parameter that accommodates corner solutions (zero consumption) for end use *k*. However, it also plays the same role as the above satiation parameter. Values of γ_k closer to zero imply a higher rate of diminishing marginal utility (or lower consumption) for a given level of baseline preference.

The baseline preference can be represented as a random utility specification as follows:

$$\phi(z_k, \varepsilon_k) = \varphi(z_k) \cdot exp(\varepsilon_k) \tag{9.2}$$

where z_k is a set of attributes characterizing end use *k* and the decision maker, and ε_k is an error term that captures the influence of unobserved factors on the baseline utility φ_k.

The exponential form for the error term guarantees the positivity of the baseline utility conditional on $\varphi(z_k) > 0$. To ensure this latter condition, $\varphi(z_k)$ is further specified as $exp(\beta' z_k)$, which then leads to the following form of the baseline random utility:

$$\varphi(z_k, \varepsilon_k) = exp(\beta' z_k + \varepsilon_k) \tag{9.3}$$

Note that a constant term can be introduced into Eq. (9.3) to represent the average influence of various unobserved factors on household energy consumption.

Then, the random utility function is reconstructed as:

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k}[exp\left(\beta' z_k + \varepsilon_k\right)]\left\{(\frac{x_k}{\gamma_k}+1)^{\alpha_k} - 1\right\} \tag{9.4}$$

The above utility specification leads to a surprisingly simple closed-form expression for the discrete–continuous joint probability (i.e., likelihood) (of consuming zero quantities for certain end uses and consuming some amount for the remaining end uses). When the error term ε_k follows an i.i.d. Gumbel distribution, the probability that an individual chooses M alternatives from K end uses is determined by Eq. (9.5) (see Bhat 2005, 2008), where the former is expressed in the form of an amount consumed and the latter is expressed in the form of monetary expenditure. From these two equations, it is obvious that the competitive relationships among choices of ownership for each end use can also be explicitly explained by the term $\left[\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{(\sum_{k=1}^{K} e^{V_k/\sigma})^M}\right]$.

$$P(e_1^*,\cdots,e_M^*,0,\cdots,0) = \frac{1}{\sigma^{M-1}}[\prod_{i=1}^{M} c_i][\prod_{i=1}^{M}\frac{1}{c_i}]\left[\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{(\sum_{k=1}^{K} e^{V_k/\sigma})^M}\right](M-1)! \tag{9.5}$$

Here σ is a scale (σ can be normalized to one if there is no variation in unit prices across end uses), and $c_i = (1-\alpha_i)/(e_i^* + \gamma_i)$, $V_k = \beta' z_k + (\alpha_k - 1)\ln(e_k^*/p_k + 1) - \ln p_k$ (k=*1*,*2*,…,K) when the α profile ($\gamma_k = 1$) is used, and $V_k = \beta' z_k - \ln(e_k^*/\gamma_k p_k + 1) - \ln p_k$ (k = *1*, *2*, …, K) when the γ profile ($\alpha_k \to 0$) is used.

In the previous section, it was assumed that the ε_k terms are independently and identically distributed across alternatives and have a standard Gumbel distribution. However, sometimes the alternatives are interrelated because of unobserved factors causing self-selection effects. Therefore, the mixed MDCEV model is further developed by assuming that ε_k (k=2, 3,…, K) follows a multivariate normal distribution (see Bhat (2005) for details).

9.3.2 A Household Energy Consumption Survey

A household energy consumption survey was conducted in Beijing in 2009. This survey was designed to collect information about the expenditures and energy consumption patterns of households in Beijing at home and outside. The questionnaire was improved following a pilot survey. The candidate households in several residential areas located in the central, inner and outer city areas were first randomly visited according to a convenient sampling method, and those who agreed to participate in the survey (nearly 1,800 households) were asked to have the questionnaires completed by the household member most familiar with household energy consumption. Several days later, the respondent households were visited again with small gifts, and their completed questionnaires were checked in a face-to-face interview. As a result, we collected valid questionnaires from 1,014 households. The questionnaire contents include the following information.

1. Individual attributes: respondent's gender, age, level of education, and degree of environmental awareness.
2. Household attributes: household size, income, composition, floor space, dwelling type, and accessibility (distances to bus stops); these are used to explore interhousehold variations in energy consumption.
3. Ownership and use of in-home appliances (e.g., refrigerators, air-conditioners and washing machines) and vehicles (e.g., passenger cars and motorcycles): attributes (e.g., efficiency, type, size, capacity) of appliances and vehicles, frequency and/or duration of use per week in different seasons. By multiplying efficiency by use, the approximate energy consumption of each end use can be derived.
4. Energy consumption: monthly energy consumption or monetary expenditure on energy sources such as electricity, gas, water, kerosene, gasoline, and diesel oil over four seasons.

9.3.3 Model Performance and Influential Factors

The dependent variables in the mixed MDCEV model are ownership of appliances/vehicles for end uses in the discrete part and monetary expenditure in the continuous part. The explanatory variables used for ownership and use were selected based on a preliminary analysis, including individual, household and residential attributes.

The estimation results are presented in Table 9.1. Disposable money and seven expenditure categories (expenditure on refrigerators, air-conditioners (AC), fans, clothes washers, gas showers, electric showers, and vehicles) are regarded as alternatives (i.e., end uses), where ownership refers to whether a household owns the item in question and use relates to monetary expenditure by the household. Disposable money, indicating the income remaining after deducting expenditure on energy for domestic appliances and vehicles, serves as the outside good that is always consumed. After several trials of model estimations, we found that the model with the satiation parameter α_k approaching zero and translation parameter γ_k at unity yields the best model fit, which suggests the existence of log-linear competitive relationships among sources of expenditure on end uses.

The constant terms related to baseline preference (elements of the β vector) in the first row are estimated by treating the disposable money alternative as the base category (i.e., the parameters in the disposal money alternative are all assumed to be zero). As pointed out by Ferdous et al. (2010a, b), these constants have no substantive interpretation and simply capture generic tendencies of spending on each category. However, all baseline preference constants are negative. This indicates that a

Table 9.1 Estimation results of the mixed MDCEV model

Explanatory variables	Refrigerator	AC	Fan	Clothes washer	Electric shower	Gas shower	Vehicle
Baseline preference constants							
Constant	−5.741**	−6.115**	−11.075**	−7.884**	−7.659**	−10.451**	−11.785**
	(−7.462)	(−10.550)	(−13.343)	(−7.224)	(−9.282)	(−12.190)	(−15.442)
Household attributes							
Income	−0.190**	0.034	−0.377**	−0.223**	−0.407**	−0.010	0.171**
	(−4.549)	(1.057)	(−8.668)	(−4.031)	(−8.731)	(−0.205)	(3.639)
Household size	−0.061	−0.235**	0.440**	0.015	−0.101	−0.631**	0.149
	(−0.492)	(−2.672)	(3.708)	(0.095)	(−0.657)	(−4.061)	(1.294)
Floor space	0.007*	0.007*	0.008	0.006	0.011**	−0.003	0.021**
	(1.692)	(1.910)	(1.567)	(0.944)	(2.261)	(−0.725)	(5.640)
Residential attributes							
Residential duration	0.031*	0.044**	0.003	0.015	−0.021	0.065**	0.028
	(1.699)	(2.860)	(0.172)	(0.549)	(−0.876)	(3.271)	(1.284)
Iron structure of dwelling	0.301	1.035**	−0.952**	0.272	0.505	−0.269	−1.438**
	(1.095)	(4.941)	(−3.503)	(0.756)	(1.445)	(−0.876)	(−5.458)
Household type	0.470	0.993**	−1.175**	0.177	−0.326	0.441	0.157
	(1.127)	(3.644)	(−3.428)	(0.393)	(−0.868)	(1.277)	(0.487)
Access	−0.120	−0.120	0.181	0.002	0.254	0.002	0.329**
	(−1.036)	(−1.445)	(1.368)	(0.017)	(1.219)	(0.001)	(2.349)
Individual attributes							
Education	0.541*	−0.069	0.179	0.390	−0.327	0.617*	0.046
	(1.694)	(−0.324)	(0.680)	(1.060)	(−1.078)	(1.937)	(0.173)
Energy-saving consciousness	−0.116	−0.868**	0.547**	−0.280	−0.443**	0.181	−0.663**
	(−0.678)	(−6.490)	(2.809)	(−1.124)	(−2.294)	(0.972)	(−4.030)
Error term							
Standard deviation	0.500**	0.122 *	0.459**	0.012	0.348	0.296*	0.335*
	(2.139)	(1.798)	(2.175)	(0.273)	(1.600)	(1.699)	(1.701)
Initial log-likelihood	−30394.6		Converged log-likelihood			−21189.2	
Rho-square	0.3029		Adjusted rho-square			0.3000	
Sample size	608						

Note: ** significant at the 5 % level. *· significant at the 10 % level. The values in parentheses are *t*-statistics

much higher percentage of households spend a nonzero amount of their budgets on disposable money relative to other alternatives.

The coefficients of explanatory variables in the mixed MDCEV model are the same for both ownership and use. A positive (negative) coefficient of an explanatory variable means that an increase in the explanatory variable increases (decreases) the likelihood that a household budget will be allocated to that expenditure category.

Household income: As household income increases, the probability of owning an AC and vehicle, and the proportions of total income expended on them (i.e., expenditure) increase, whereas the probability of owning a refrigerator, fan, clothes washer or shower and expenditure decreases. This may reflect the fact that households with higher income prefer luxurious ACs and vehicles to other types of end uses. This observation may explain the relationship between household income and energy consumption.

Household size: The household size coefficients are positive for fans and negative for ACs and gas showers, suggesting that households with more members show a higher preference for ownership and use less energy-intensive appliances (i.e., fans) than energy-intensive ones (i.e., ACs and gas showers). This may be because larger families have less disposable income, leading them to invest in more affordable end uses to meet their functional needs. There is no significant impact of household size on ownership and use of vehicles.

Floor space: As floor space increases, ownership and use of all appliances for end uses, except gas showers, increase. In particular, floor space has a significant and positive effect on the energy consumption of vehicles. This suggests that floor space differs from household income in explaining the ownership and use of appliances.

Residential duration and household type are important in the ownership and use of domestic appliances but have no obvious effect on the ownership and use of vehicles. As period of residence increases, the probability of owning a refrigerator, AC or gas shower and expenditure increase. This may be because longer periods of residence always accompany older appliances or vehicles, which consume more energy. Household type has a positive effect on ownership and use of ACs but a negative effect on fans, implying a complementary relationship between these two appliances for householders who own their houses. Steel structure of dwellings shows a significant influence on ownership and use of ACs, fans and vehicles. To compensate for large expenditure on AC, the probability of owning and spending money on a vehicle is reduced. The access factor related to residential location has no obvious impact on energy consumption but has a negative influence on energy consumption by vehicles. The further the household is from a bus stop or subway station, the greater the probability of buying/using a vehicle.

Household members' highest education level has no significant influence on energy consumption except for refrigerators and gas showers. Energy awareness is an attitudinal factor that motivates households to behave in environmentally friendly ways. It is estimated that individuals who are willing to save energy own and use fewer energy-intensive items (e.g., ACs and vehicles) than other people. This attitudinal factor affects both residential energy consumption and travel behavior.

Some household and personal attributes, such as income, floor space, steel-framed dwellings, and energy awareness significantly influence both residential energy consumption and travel behavior. This means that a change in sociodemographic characteristics or dwelling type changes both residential and transport energy-use patterns, providing important evidence of the necessity of joint representation.

The standard deviation of the error terms introduced in the baseline preference function shows that ownership and use of refrigerators, ACs, fans, gas showers and

Table 9.2 Correlations among end uses due to unobserved factors

	Refrigerator	AC	Fan	Clothes washer	Electrical shower	Gas shower	Car
Refrigerator	1						
AC	0.318	1					
Fan	−0.087	−0.105	1				
Clothes washer	0.039	0.109	0.208	1			
Electrical shower	−0.090	0.106	0.370	0.317	1		
Gas shower	−0.241	−0.095	0.140	−0.059	0.172	1	
Car	0.412	0.301	0.096	0.061	−0.109	−0.426	1

vehicles are significantly affected by unobserved factors. Furthermore, the correlation between the energy consumption of different end uses because of unobserved factors was identified (see Table 9.2), especially for refrigerators and ACs, electric showers and clothes washers and fans in residences. Correlations in energy use were also observed between cars and refrigerators, cars and ACs, and cars and gas showers across the residential and transport sectors.

9.3.4 Implications for Energy Policy

The empirical analysis in Beijing confirmed the effectiveness of the mixed MDCEV model in simultaneously describing residential energy consumption and travel behavior. Furthermore, on the one hand, log-linear competitive relationships are found among expenditure on end uses, while on the other hand, the correlation between energy consumption of end uses caused by unobserved factors is also verified. That is, the necessity for joint representation of residential and transport energy consumption is identified. The above correlation also suggests that, for example, reduction of residential energy consumption because of the introduction of energy-saving end uses results in an increase of disposable household income. However, this may lead to an increase in gasoline consumption by vehicles. Thus, to reduce household energy consumption, governments should focus on the mutual influence between residential and transport energy consumption. This finding is expected to provide a new viewpoint for designing policies. For example, the Japanese government is promoting the purchase of eco-friendly electric appliances through the legalized "eco-point" scheme, which allows consumers to spend the credits gained from buying one appliance on other types of appliances. However, currently, such credits cannot be spent on the purchase and/or use of vehicles. It may also be a good idea to extend the "eco-point" scheme to cover both domestic and travel-related end uses. Interestingly, some electricity, housing, and automobile companies in Japan have already developed joint management systems for electricity fees of both domestic appliances and electric cars. Such systems can assist households to save and use electricity in more efficient ways.[1] It is therefore not unrealistic to integrate the above "eco-point" scheme and electricity management systems for more effective promotion of eco-friendly domestic end uses and vehicles.

Within such an integrated framework of household energy consumption behavior, the efficacy of land-use policy on energy saving is further discussed in the next section.

9.4 Land-Use Policy and Household Energy Consumption Behavior

In the behavioral sciences, the importance of relationships between long-, medium- and short-term choices is emphasized (Eliasson and Mattsson 2000; Waddell 2001). With regard to household energy consumption, following the definition of Ben-Akiva and Lerman (1991), a long-term decision is defined as a choice of residence, a medium-term decision as the choice of ownership of an item intended for an end use, and a short-term decision as one that relates to end use (e.g., frequency, duration, or distance traveled). It is plausible that a decision of residential location not only determines the connection between the household and the urban environment but also influences the household's activity time allocation (Pinjari et al. 2009) as well as the concomitant energy consumption behavior. If so, it is reasonable to infer that residential location choice may influence household energy consumption. Although integrated analyses of land-use planning and travel behavior have attracted a great deal of interest, land use and energy consumption by domestic end users has not gained the same level of attention from either academics or practitioners (Cooper 2011). However, both residential and transport energy consumption deserve to be emphasized. Furthermore, because of financial and time constraints, it is necessary to consider these two factors together (see Yu et al. 2011 for elaboration).

Essentially, the interrelationship between residential location and household energy consumption can be very complicated. However, the majority of previous researchers have assumed a one-way causal effect from residential environment (*RE*) characteristics to household energy consumption. Specifically, households and individuals locate themselves in neighborhoods and then determine their energy consumption according to neighborhood attributes. In this context, if it is found that accessibility to buses/subway stations has a negative influence on household energy consumption, the implication would be that building neighborhoods near stations could decrease the aggregate energy demand in the population. The problem is that the ways in which individuals/households make residential choices and energy consumption decisions is not comprehensively understood. In reality, environmentally friendly households and individuals may self-select to settle in neighborhoods with

[1] http://company.nikkei.co.jp/news/news.aspx?scode=7203&NewsItemID=20101019NKM0223&type=2 (Accessed on 10 Feb 2011).

good accessibility to public transport, and hence they can pursue their energy-saving lifestyles. If this were true, urban land-use policies aimed at increasing the accessibility of public transport would not show the expected result of reducing household energy consumption. This kind of noncausal association between residential choice and energy consumption derived from intervening variables (e.g., social, cultural, psychological or sociodemographic factors) that cause both is termed a "self-selection effect." Interaction between residential choice and household energy consumption behavior should therefore not simply be interpreted by regarding residential environment indicators as exogenous explanatory variables. The observed relationship may be part causal and part self-selection. That is, after controlling for the spurious association due to the self-selection effect of demographics and other unobserved characteristics, we are more confident of assessing the causal impact of *RE* on household energy consumption. More credible and persuasive policies can then be developed. Moreover, the self-selection effect may vary with end uses. For example, householders who do not like cooking may choose to reside in a neighborhood with good catering facilities (e.g., restaurants and/or supermarkets) and to rely less on cooking-related end uses, while householders with a preference for driving may prefer to live in a suburban area to satisfy it. Obviously, these two effects are distinct. Thus, it is better to consider multiple self-selection effects that reflect the diverse self-selection effects for different end uses. Additionally, the above-mentioned behavioral aspects may be heterogeneous across household and may be caused by observed and unobserved factors. Currently, there is still no examination of the self-selection effect in an integrated analysis of residential location choice and household energy consumption behavior. Consequently, our study is devoted to filling this gap.

The above-mentioned behavioral mechanisms actually pose some policy issues that have not been highlighted in practice. First, is the land-use policy effective in controlling household energy consumption, and to what extent does it work? The "true" effect of the land-use policy may be wrongly predicted if the self-selection phenomenon is ignored. Second, is the self-selection effect significant for households, and for what types of end uses? By answering these two questions, the need for "soft policy" (e.g., enhancing residents' environmental awareness, making residents aware of their excessive energy consumption patterns, and promoting energy-saving behavior) and the kinds of end uses that should be emphasized when implementing "soft policy" could be identified. Third, is it necessary to represent the energy consumption behaviors in residential sector and private transportation sector jointly? This issue may provide a unique lens on the necessity for the development of a package policy that could reduce energy consumption in the above two sectors simultaneously.

To develop a robust policy system to reduce total household energy consumption, this chapter addresses the aforesaid policy issues by accommodating all the behavioral mechanisms mentioned above in a consistent and unified framework. Specifically, we first build an integrated model, termed the mixed MNL-MDCEV model, which covers residential location choice, ownership of items such as domestic appliances and private cars for end uses, and use behavior, and then apply it to examine the sensitivity of household energy consumption to changes in land-use policy by considering a comprehensive set of residential environment (*RE*) variables and sociodemographic variables as well as multiple self-selection effects.

9.4.1 The Mixed MNL–MDCEV Model

As discussed previously, household energy consumption related to the ownership and use of varied appliances or vehicles may be correlated with residential location choice. In particular, self-selection effects cannot be ignored. To accommodate such mechanisms, the mixed MNL–MDCEV model was constructed to combine these two aspects (here only the model framework is interpreted; see Yu et al. (2012) for more details).

Let $i(i=1,2,\ldots,I)$ denote the index for the households, $j(j=1,2,\ldots,J)$ the index for the neighborhood of residential choice, and k ($k = 1, \ldots, K$) the index for the end use. Then the utility functions of the above two behavioral aspects can be defined as follows, with the influences of the self-selection effects explicitly incorporated:

$$u_{ij}^{R} = f_{ij}(UR_{ij}, \pm\omega_{ijk}(k=1,..,K), \pi_{ij}) \tag{9.6}$$

$$u_{ij}^{E} = g_{ij}(UE_{ijk}, \pm\omega_{ijk}, \varepsilon_{ijk} \mid k=1,\ldots,K) \tag{9.7}$$

Here u_{ij}^{R} and u_{ij}^{E} indicate the utility functions of household i's residential location choice and energy consumption with respect to residential neighborhood j, respectively. The terms UR_{ij} and UE_{ijk} are observed components of utility functions explained by social demographic factors and residential environment attributes, and π_{ij} and ε_{ijk} are unobserved random components that represent the effect of households' unobserved heterogeneity on residential location choice and household energy consumption behavior, respectively. There is another unobserved random component ω_{ijk}, which is shared by the two behavioral aspects and used to represent the influence of self-selection effects. Specifically, ω_{ijk} includes individual or household-specific unobserved factors affecting household i's sensitivity to both residential choice and the ownership and use of end-use item k. Because of the factors in ω_{ijk}, such as attitudes and lifestyle preferences, households self-select one type of neighborhood and pursue a ω_{ijk} -consistent energy consumption pattern. As mentioned above, because the self-selection effect may vary with end uses, a unique ω_{ijk} is allotted to each end use, and the multiple self-selection effects are represented exactly by the group ω_{ijk} $(k=1,2,\ldots,K)$.

Because of the above multiple self-selection effects, it is necessary to integrate household energy consumption and residential choice behaviors into a unified modeling framework that can incorporate not only the causal impact from residential choice on household energy consumption but also the noncausal association–self-selection effects. With this modeling approach, it is expected that the relatively "pure" causal effect of *RE* measures on energy consumption behavior can be captured in a more appropriate way. The well-known multinomial logit model is adopted to represent residential location choice, and the MDCEV model proposed by Bhat (2005, 2008) is utilized to describe the energy consumption behavior.

9.4.2 A Quasi Panel Survey

A quasi panel household energy consumption survey was conducted in the summer of 2010 to collect energy consumption information. This survey was retrospective and asked householders to provide information at two time points: at the time of the survey and a previous time point (i.e., the year 2001 for households that had not relocated within the previous 10 years, and the year before the relocation for households that had moved within the previous 10 years). Compared with the first survey, besides the end uses previously mentioned, some appliances for recreational activities and cooking, such as TVs, PCs and microwave ovens were targeted in this survey. Questions on three other categories of information were included: the individual attributes of every member in the household, specific information about the residential environment, and the activity/travel behavior of each member of the household.

9.4.3 Analysis of Model Estimation Results

Several types of variables are introduced in the integrated model based on a preliminary analysis, including: (1) residential environment attributes in the current situation (living in the CBD or suburban areas (dummy variable), numbers of shopping malls, supermarkets, recreational facilities, restaurants, parks, bus lines, and train lines within the neighborhood); (2) household attributes at the time of relocation (annual household income, household size, presence of children and senior people, number of household members in employment, highest education level in household); (3) housing attributes at the time of relocation (residential duration, floor space, and whether the house is rented). Model estimation results are shown in Tables 9.3 and 9.4, in which the estimated mean and variance (or standard deviation) are given for each variable. Specifically, a significant mean reflects that the fixed effect of the factor in the whole population is obviously different from zero, while a significant variance (or standard deviation) indicates that the factor has an apparent random effect in the population (that is, the hypothesis of no variance in the population can be rejected). By comparing the standard deviation with its mean, population heterogeneity can be captured.

Bearing in mind the focus of this study (i.e., the influence of self-selection effects and built environment factors on household energy consumption behavior), we merely target household energy consumption. In the household energy consumption submodel, 11 expenditure categories (expenditure on refrigerators, fans,

Table 9.3 Estimation results of household energy consumption behavior: the mixed MNL–MDCEV model

	Fridge	Fan	AC	Electric stove	Electric shower	Gas shower	Clothes washer	TV	PC	Microwave oven	Car
Residential environment attributes											
CBD area	2.211*	−0.213*	−0.471*	−0.16*	−0.474*	−0.547*	−3.037*	−0.537*	−1.846*	−1.634*	3.882*
(1 yes, 0 no)	0.761	0.31*	0.458*	0.297*	0.249*	0.045	1.66*	0.21*	0.409*	0.472*	4.628*
Suburban area	0.06	−0.36*	0.44*	0.028*	−5.164*	0.53	−1.767*	2.343*	0.846*	−0.943*	2.849*
(1 yes, 0 no)	0.746*	0.318*	0.173*	0.071*	3.846*	2.286	0.534*	0.506*	0.363*	0.699*	0.576*
Number of	−5.551*	−0.244*	−0.038*	−0.059	0.561	1.158*	4.898*	−0.964*	−5.447*	2.059*	1.255*
shopping malls	0.894*	0.245*	0.077*	0.892*	0.883	0.678*	2.196*	0.415*	2.055*	0.729*	1.252*
Number of	2.78*	0.027*	1.436*	0.673	−10.312*	−2.568*	−0.446*	−0.468*	3.469*	0.035	−2.473*
supermarkets	1.266*	0.063*	0.47*	1.772*	1.523*	3.215	0.658*	0.427	0.609*	0.392*	0.636
ln (number of	−1.427*	−2.704*	−4.606*	0.481*	4.637*	−1.503*	0.918*	−1.029*	−0.173*	−0.124	−4.543*
recreational facilities)	0.962	0.414*	1.153*	0.473*	0.675*	0.925*	1.085	0.373*	0.3*	0.484*	0.963*
ln (Number	0.147	−1.511*	1.958*	−1.479*	2.561*	0.24	−1.924*	−0.392*	1.834*	−0.869*	6.599*
of restaurants)	0.541*	0.587*	2.191*	0.74*	1.424	2.254	1.83*	0.253*	0.342*	0.492*	0.455*
Number of parks	2.151*	0.216	−1.331*	−1.528*	1.275*	1.807*	−0.5*	−0.818*	0.009	−5.017*	3.002*
	0.64*	2.291*	0.586*	0.523*	0.636*	1.19*	0.265*	0.281*	0.405*	0.643*	3.521*
Number of bus lines	0.691	1.988*	−0.012	2.45*	1.296*	0.301*	−0.17*	1.991*	−2.021*	3.956*	−26.082*
	0.541*	0.613*	0.479*	0.563	0.458	0.55*	0.285*	1.451*	0.379*	0.469*	7.163*
Number of train lines	8.874*	−0.646*	0.097	2.518*	0.922*	−0.987*	1.331*	−0.916*	2.449*	0.142	3.213*
	0.851*	0.348*	0.709*	2.77	0.586	0.77*	0.378*	0.333*	1.458*	0.534	4.763*
Unobserved attributes											
Unobserved η_{ijk}	4.603*	−2.572*	−1.626*	4.509*	−11.229*	0.028	−5.053	−2.169*	0.41	0.097	−10.847*
	2.929*	3.31	1.408*	2.045*	6.231*	0.51*	2.572	3.027*	2.339*	3.675*	1.774*
Unobserved ω_{ijk}	6.663*	−30.112*	39.05*	21.316*	2.84*	−2.637*	8.764*	8.189*	5.608*	−5.603*	−9.826*
	2.844*	3.968	3.798*	3.732	2.461*	5.098	2.333*	2.218*	1.984*	3.886	4.023*

Household socio-demographics and housing characteristics											
Household annual income	−8.158*	−3.307*	1.884*	1.461	−3.171*	0.785*	−0.965*	2.297*	−4.284*	1.035*	0.409*
(1:lowest to 6 highest)	1.124	1.336	0.693*	2.476*	0.459*	0.528*	0.382*	0.526*	0.541*	1.059*	0.182*
Household size	−0.827*	2.179*	0.888*	1.296*	3.664*	0.115*	0.311*	4.606*	−0.499*	−0.274*	4.25*
	0.786	0.645*	0.346*	1.375*	1.663*	0.055*	0.155*	0.414*	0.597	0.063*	1.796*
Presence of children	2.102*	2.376*	−0.434*	24.362*	−1.175*	−0.474*	1.263*	−0.056	−0.042*	−1.61*	−0.608*
(age ≤ 16) (1 yes, 0 no)	0.468*	0.311*	0.521*	3.865*	2.542*	0.483*	0.307*	0.255*	0.071*	0.925	0.756*
Presence of senior	0.353*	2.818*	−4.237*	−2.728*	−1.935*	−0.957*	−0.044	−0.013	1.558*	1.621*	4.133*
people (1 yes, 0 **no**)	0.341*	0.635*	0.457*	1.044	0.645*	0.66*	0.226*	0.063*	0.84*	0.936*	0.810*
Number of workers	−0.362*	−4.818*	0.127	1.962*	−0.459*	−0.034*	−1.368*	1.043*	1.569*	0.726*	8.487*
	0.369*	0.539*	0.329*	0.552*	0.429*	0.134*	0.605*	0.981*	0.679*	0.362*	0.896*
The highest education level	0.276	1.780*	−2.664*	−0.910*	2.216*	0.235*	−0.007	0.511*	−0.532*	3.165*	−2.227*
(1 ≥ bachelor, 0 other)	0.540*	0.617*	1.104*	0.769	0.606	1.108*	0.063*	0.443*	0.632*	1.479*	1.034*
Residential duration (years)	1.415*	0.908*	1.677*	4.999*	−4.330*	−0.060	−1.783*	1.977*	0.461*	−1.842*	−0.389*
	0.457*	0.307*	0.476*	2.528	0.569*	0.466*	1.387*	0.556*	0.318*	0.451*	1.560*
Housing area (m^2)	0.181*	0.439*	1.135*	4.706*	−3.864*	−5.223*	1.271*	−0.667*	−0.133*	0.054	0.028
	0.268*	0.358*	0.440*	0.391*	2.802	3.013*	1.508*	0.871*	0.326*	0.295*	0.182*
Whether the house	−1.085*	4.450*	−1.254*	−1.965	2.774*	−0.362*	−0.866*	0.438*	−0.174*	−0.006	2.038*
is rent (1 yes, 0 no)	0.355*	0.485*	0.362*	1.595*	1.324	0.462*	0.307*	0.315*	0.281*	0.089*	0.638
Initial log-likelihood	−41340				Converged log-likelihood			−36188			
Rho-squared	0.1246				Adjusted Rho-squared			0.1188			
Sample size	530										

Note: There are two values associated with each parameter: the upper one refers to the estimated mean and the lower one to standard deviation; * significant at the 5 % level

Table 9.4 Simulation results for the assumed policy scenarios defined by changing the residential environment attributes

	Aggregate change in the household energy consumption of each end use (number in parentheses is the exact MJ change)							
	Recreational facilities increase by 10 %	Bus line increase by 1	Shopping mall increase by 1	Restaurant increase by 10 %	Park increase by 1	Supermarket increase by 1	Train line increase by 1	Total (percentage)
Car	−0.02 % (−4.07)	−3.18 % (−591.85)	−0.01 % (−0.44)	0.13 % (23.34)	0.00 % (0.43)	−0.10 % (−18.40)	0.00 % (0.08)	−3.18 %
Fridge	−0.16 % (−2.27)	1.97 % (27.62)	0.01 % (0.21)	0.01 % (0.12)	0.01 % (0.09)	0.02 %(0.34)	0.01 % (0.19)	1.87 %
Fan	1.26 % (2.12)	2.28 % (3.83)	−1.23 % (−2.07)	−1.68 % (−2.82)	1.37 % (2.31)	2.42 % (4.06)	1.22 % (2.05)	5.64 %
AC	−1.07 % (−26.94)	−0.48 % (−12.03)	0.05 % (1.26)	0.06 % (1.59)	−0.05 % (−1.26)	0.38 % (9.52)	0.05 % (1.26)	−1.05 %
Electric stove	1.47 % (12.38)	2.10 % (17.69)	−0.12 % (−1.05)	0.03 % (0.23)	0.01 % (0.11)	0.07 % (0.57)	0.04 % (0.37)	3.59 %
Electric shower	0.08 % (0.74)	1.17 % (10.96)	0.14 % (1.28)	0.27 % (2.51)	0.13 % (1.27)	−0.12 % (−1.15)	0.13 % (1.25)	1.79 %
Gas shower	−0.01 % (−0.57)	−0.09 % (−7.95)	0.07 % (5.82)	0.09 % (7.73)	0.07 % (5.90)	0.04 % (3.63)	0.07 % (5.85)	0.24 %
Clothes washer	0.11 % (0.34)	1.37 % (4.38)	0.62 % (1.99)	−0.62 % (−1.97)	0.66 % (2.10)	0.26 % (0.81)	0.62 % (1.96)	3.01 %
TV	−1.28 % (−25.32)	−0.47 % (−9.30)	−0.08 % (−1.55)	−0.14 % (−2.87)	−0.09 % (−1.87)	−0.07 % (−1.43)	−0.08 % (−1.55)	−2.21 %
PC	−0.01 % (−0.14)	−1.01 % (−18.64)	0.01 % (0.25)	0.03 % (0.62)	0.01 % (0.27)	0.01 % (0.26)	0.01 % (0.25)	−0.93 %
Microwave oven	0.73 % (0.74)	5.02 % (5.07)	0.06 % (0.06)	−0.07 % (−0.07)	−0.15 % (−0.15)	15.08 % (15.22)	0.05 % (0.05)	20.72 %
Total (MJ)	−43.01	−570.22	5.76	28.40	9.19	13.43	11.77	

air-conditioners (AC), electric stoves, electric showers, gas showers, clothes washers, TVs, PCs, microwave ovens, and cars) and savings are set as the alternatives in the MDCEV model. Savings, meaning the income remaining after deducting energy expenditure, serve as outside goods, and the reference alternative for which the parameters in baseline utility are set at zero. In the model, ownership refers to whether a household owns an item for an end use in question, and use relates to how much the household spends in monetary terms. Table 9.3 lists the estimated mean and standard deviation of all variables, including residential environment attributes, household attributes, residential attributes, heterogeneity and multiple self-selection effects. It can be seen that all these variables are significant in the energy consumption behavior for different end uses. Because of limited space, we only consider the self-selection factors and, based on the model estimation results, design land-use policy scenarios by controlling these self-selection effects.

9.4.3.1 Multiple Self-Selection Effects

ω_{ijk} ($k = 1,2,\ldots,K$) denotes the unobserved factors associated with both residential choice and household energy consumption behavior, which are regarded as the cause of multiple self-selection effects. Based on the mean of ω_{ijk}, it is found that there is a significant unobserved component that simultaneously affects residential location choice and the ownership and use of all 11 appliances or vehicles associated with end uses, indicating that long-term residential location choice behavior and medium/short-term household energy consumption behavior are correlated; in addition, the self-selection effects differ across end uses, verifying the necessity of incorporating multiple self-selection effects into the integrated model. Thus, the spurious effect of *RE* attributes occurs in household energy consumption behavior because of multiple self-selection effects. Several trials show that the estimation result with positive signs in the term $\pm\omega_{ijk}$ in Eqs. (9.6) and (9.7) for all end uses yields the best model fit, which indicates that the unobserved factors have a positive influence on residential choice and lead to a high preference for the ownership and use of the *k*th item for an end use. In spite of the plus signs for $\pm\omega_{ijk}$, the ω_{ijk} itself can be either positive or negative. Specifically, for domestic appliances (i.e., refrigerators, ACs, electric stoves, clothes washers, TVs, and PCs), the positive self-selection effect indicates that some unobserved factors make households self-select to a special neighborhood and be more likely to own and spend more money on these appliances. However, for fans, gas showers, microwave ovens and cars, the negative sign shows that certain unobserved factors make households select a special neighborhood and be less likely to own or spend money on cars. With regard to the standard deviations of ω_{ijk}, it is confirmed that the multiple self-selection effects on the residential choice and energy consumption of refrigerators, ACs, electric showers, clothes washers, TVs, PCs and cars vary significantly with households. Furthermore, such heterogeneous self-selection effects are more obvious in the ownership and use of electric showers and cars. This also supports the rationality of accommodating multiple self-selection effects into the integrated model instead of using a common effect for all end uses. The self-selection effect may come from social factors such as lifestyle and life stage (e.g., Lutzenhiser 1993; Weber and Perrels 2000), cultural factors (e.g., Abrahamse et al. 2005; Lutzenhiser 1992), motivational factors (e.g., Seligman et al. 1979; Spangenberg 2002) or other factors. Although from the model results we cannot clarify the exact self-selection effect or how to change it, after controlling for the self-selection effect in the model, a quite accurate estimate of the effect from residential environment variables can be made. Consequently, a less biased evaluation of the effect of land-use policy on household energy consumption can be derived.

9.4.3.2 Diversified Factors: An Analysis of Variance Proportion

To clarify further the effects of the explanatory variables, we next calculate the proportion of variance explained by each variable in the total variance of the baseline preference for both ownership and use as follows:

$$\begin{aligned} var\left[ln\left(\varphi_{ijk}\right)\right] &= var(\mu_k' s_{ij}) + var(\Delta_k' x_i) + var(\eta_{ijk}) + var(\pm\omega_{ijk}) + var(\tau_{ijk}) \\ &= var(\mu_k' s_{ij}) + var(\Delta_k' x_i) + (\sigma_{\eta k}^2 + \sigma_{\omega k}^2 + \frac{\pi^2}{6}). \end{aligned} \tag{9.8}$$

To identify the degree to which various factors influence household energy consumption behavior, the proportion of variance explained by each factor is calculated. For ease of interpretation, instead of a list of the variance proportions for all factors, the total effects from three groups of variables—household attributes, residential environment attributes, and unobserved factors (collective impact of η_{ijk} and ω_{ijk})— together with the sole effect of ω_{ijk}, which causes the self-selection effect, are presented in Fig. 9.2. It can be seen that different attributes have their own domain. For the energy consumption of refrigerators, fans, ACs, electric stoves, electric showers, gas showers and TVs, household and individual attributes dominate. For clothes washers, PCs, microwave ovens and cars, residential environment attributes are more important in explaining the ownership and use behavior. The proportion of variance of unobserved factors varies considerably with end uses, ranging between 5 % and 41 %, among which the proportion causing self-selection effects changes from 2 % to 24 %, suggesting a significance that cannot be neglected when modeling the interaction between residential choice and household energy consumption behavior.

9.4.3.3 Sensitivity Analysis of Policy Interventions

To examine the sensitivity of household energy consumption to policy interventions, seven policy scenarios were designed by changing residential environment attributes. These were: an additional shopping mall, an additional supermarket, a

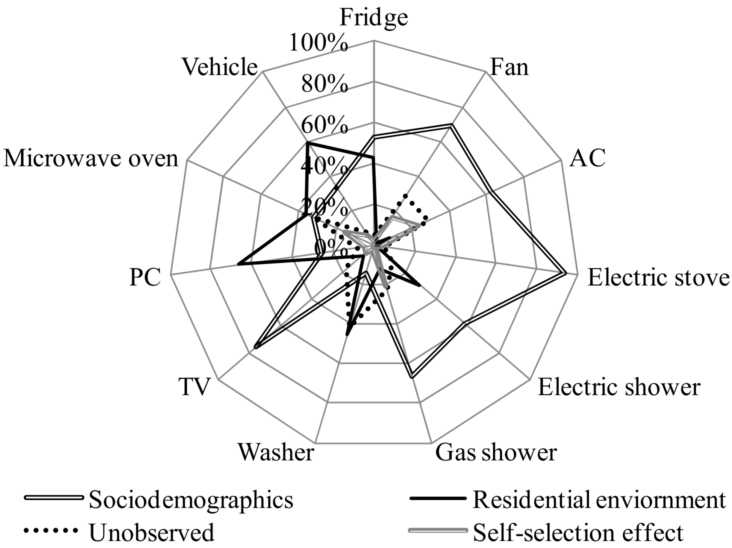

Fig. 9.2 The variance portion for end uses

10 % increase in the number of recreational facilities, a 10 % increase in the number of restaurants, an additional park, an additional bus line, and an additional train line.

A sensitivity analysis was conducted by calculating the aggregate change between the predicted household energy consumption in each scenario and consumption in the Reference Scenario (the scenario without any change in the variables). Table 9.4 lists both the percentage change and the exact MJ (megajoule) change. The following can be seen.

1. Compared with the current situation, an increase in the number of shopping malls in the neighborhood leads to a decrease in energy consumption for fans (1.23 % less), electric stoves (0.12 % less), TVs (0.08 % less), and cars (0.01 % less), but these savings are offset by the incremental effect of other end uses (especially of gas showers), and total energy use is 5.76 MJ more than before.
2. An increase in the number of supermarkets in the neighborhood can reduce the energy use of electric showers (0.12 % less), TVs (0.07 % less), and cars (0.10 % less), but this effect is also compensated for, especially by ACs and microwave ovens. Overall, there is an increase of 13.43 MJ.
3. After increasing the number of surrounding amenity facilities by 10 %, the energy consumption by ACs and TVs declines considerably (1.07 % less and 1.28 % less, respectively), and 43 MJ energy can be saved overall.
4. Although the energy consumed by fans, clothes washers, TVs and microwave ovens decreases slightly if the number of restaurants in the neighborhood increases by 10 %, car use is 0.13 % (i.e., 23.34 MJ) more than before, which completely cancels out the savings, and overall an extra 28.4 MJ of energy will be consumed.

5. The increase in energy consumption change from an additional park in the neighborhood is approximately 9 MJ primarily because of the contribution of gas showers.
6. An additional bus line has the greatest influence on household energy consumption, especially on private car gasoline use, of which 3.18 % (i.e., 600 MJ) of energy consumption is saved. In addition, a significant saving on PCs (1.01 % less) is found in this scenario.
7. An additional train line serving the residential area under study has a quite small effect on car use (less than 0.01 % change). Nevertheless, because of the increased energy consumption for domestic end uses, an additional 11.77 MJ is consumed.

Overall, we found that changing some *RE* attributes (e.g., recreational facilities and bus lines) can save significant amounts of energy on the one hand, and changing *RE* attributes (e.g., supermarkets and restaurants) can increase energy consumption considerably on the other hand. In addition, the magnitude of the percentage changes for ACs, gas showers and PCs indicates a relative inelasticity to changes in *RE* attributes, while the opposite is true for fans, microwave ovens and cars. Furthermore, the necessity for joint representation of energy consumption in both the residential and transport sectors is emphasized because of the significant complementary effect between them. Specifically, if we are only concerned with energy consumed by cars in response to changes in *RE* attributes, it is revealed that increasing the number of shopping malls, supermarkets, recreational facilities, and bus lines has a negative influence. However because of the complementary effect from other domestic end uses, increasing the number of shopping malls and supermarkets does not ultimately reduce the energy consumption but rather leads to an increment. Thus, many previous studies that focus exclusively on the relationship between land use and the transport or residential sector may be insufficiently comprehensive.

9.4.3.4 Paying More Attention to Unobserved Factors

First, the empirical analysis confirmed the effectiveness of the integrated model in describing residential location choice and household energy consumption behavior by simultaneously incorporating a one-way causal relationship and a noncausal association (i.e., the self-selection effect) between them. This provides a strong support for the accurate preevaluation of the policy effects.

Second, the statistically significant effects of residential environment attributes on household energy consumption indicate that land-use policy plays an important role in changing Beijing residents' energy consumption patterns. Therefore, in addition to technological improvement and economic tools, land-use policy can be regarded as an instrument for influencing household energy consumption. However, the significant unobserved factors associated with self-selection effects suggest that residential environment attributes are not completely exogenous in household energy consumption behavior. In other words, the effect of land-use policy on household energy use would be incorrectly estimated because of self-selection effects. In addition, self-selection effects are found to vary with end uses (and the resulting change in energy consumption ranges from 2 % to 24 %). This demonstrates the necessity of considering end-use-specific self-selection effects. The above finding suggests that when planners attempt to develop land-use policy to save energy, in addition to the observed factors (e.g., *RE* attributes, Sociodemographic factors, or housing attributes), they should include unobserved factors (e.g., the social factors, cultural factors, psychological factors, etc.) that may cause the self-selection phenomenon, in order to understand the energy consumption behavior. This also implies that introducing "soft policy" is important for reducing household energy consumption in Beijing. This could include the provision of information about energy saving and an evaluation tool for households to monitor their energy consumption and emissions (as OECD countries do[2]). Moreover, soft policies focusing on electric fans, air-conditioners, gas showers, microwave ovens and cars in Beijing should be given priority because of the larger proportion of variance in the factors associated with the self-selection effect on energy consumption.

After self-selection effects are controlled for, the land-use policy scenario analysis shows that by changing the number of recreational facilities and bus lines in the neighborhood, household energy conservation can be significantly improved, while increasing the number of supermarkets and restaurants in a neighborhood will increase energy consumption considerably. It is further found that the energy consumption of ACs, gas showers and PCs is quite inelastic to changes of residential environment attributes, while the opposite is true for fans, microwave ovens and cars.

Finally, the need for joint representation for residential and transport energy consumption is emphasized, owing to the significant complementary effect between these two sectors shown in the policy scenarios. In other words, if we only focus on the residential or transport sector, a specious change in energy demand change in response to a policy would be derived that may actually lead to a great increase in total energy consumption. From this viewpoint, some package policies that could reduce energy consumption in both sectors can be developed, such as an extension of the Japanese "eco-point" scheme[3] to cover both domestic appliances and vehicles.

[2] http://www.consumerspower.org/home_energy/billestimator.php (Accessed on 10 Nov 2011); http://hes.lbl.gov/consumer/ (Accessed on 10 Nov 2011).

[3] http://www.japanfs.org/en/mailmagazine/newsletter/pages/029766.html (Accessed on 2 Feb 2012). The Japanese government is promoting the purchase of eco-friendly electric appliances through the legislated "eco-point" scheme, which allows consumers to spend credits gained from buying one appliance on other appliances. However, such credits cannot currently be spent on the purchase and/or use of vehicles.

9.5 Conclusion and Future Research Issues

This chapter provides a broader perspective on household energy consumption. The proposal for joint representation of residential and transport energy consumption is supported by both the preliminary analysis and the policy analysis, suggesting that a cross-sector package policy covering both residential and transport sectors should be developed. In this integrated framework, the effect of land-use policy is further evaluated and verified as effective in saving energy even after we control for self-selection effects. However, not all land-use policies play a positive role in energy saving, implying that accurately gauging policy effects is essential. Because of significant self-selection effects, the importance of introducing "soft policy" to conserve household energy consumption is identified.

In addition to the main conclusions, several research issues should be identified. In this study, energy consumption is calculated based on end-use efficiency and use reported by respondents. Reporting bias can occur in both dependent and explanatory variables in any type of questionnaire survey. This is also true in this study. Such reporting bias should be corrected by improving data collection methods and/or adopting more advanced modeling techniques. Some technologies, such as GIS, GPS, and ICT, could be used to reduce the burden on respondents and consequently to reduce reporting error. Data fusion techniques may be helpful in correcting reporting errors by combining different data sources, if available. Reporting biases could be accommodated in the modeling process (e.g., utilizing the concept of measurement equation in the structural equation models with latent variables, and discretizing the continuous variables). However, all the above ideas incur increased cost for data collection and model estimation. For the self-selection effects, we simply use a random term to capture the aggregate unobserved factors that cause them, but this integrated model can be extended to clarify the exact source of the self-selection effects (see Pinjari et al. 2009). Because of the limited sample size, the more variables that were included in the model, the more unreliable the results. Consequently, we did not develop a complex model. Another shortcoming is that the rebound effects are considered to be implicitly instead of explicitly quantified. Further analysis to assess the relationship between end-use efficiency and energy consumption in the context of the integrated model framework should be conducted. Land-use policy is only an example of the energy policy development in the joint representation structure. As we have shown, land-use policy alone is far from sufficient to achieve energy reduction targets. Therefore, other policies and policy packages should be designed to resolve this problem.

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Chapter 10
ICT-Based Traffic Safety Measures and Drivers' Responses

Junyi Zhang, Wonchul Kim, and Akimasa Fujiwara

Abstract With the rapid progress of information and communication technologies (ICT), measures and policies targeting specific individuals rather than the public have become possible. Focusing on traffic safety measures, this study examines the effects of in-vehicle traffic warning information (IVTWI) on reducing driving risk, which is defined based on changes of driving speed. An ordered response probit model is used to represent driving risk by explicitly reflecting the influence of short-term memory and long-term driving experience. Based on data collected from an on-site driving experiment targeting a signalized intersection with limited signal visibility in Hiroshima City, Japan, the model estimation results showed that driving risk could be reduced by providing IVTWI in that the utility of this information gradually decreased up to 20 s after it was provided. However, IVTWI remained effective for 7.5 s. It was found that in an interactive traffic situation, the decay of information utility was faster than in a free-driving situation. This indicates that the timing and human–machine interface of IVTWI provision should be considered based on the degree of traffic congestion. Regarding the influence of driving experience on drivers' short-term memory, the results showed that extensive driving experience improves drivers' memory of IVTWI.

Keywords Driving risk • Short-term memory • Traffic accident • Warning information

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10.1 Traffic Accidents, Human Errors and Roles of ICT-Based Measures

In the field of traffic safety, the motto “zero accidents and no injuries” would be the ideal target for happiness and health. To prevent traffic accidents, the design of interventions has traditionally used three major approaches known as “3E”; that is, Education, Enforcement and Engineering. Education is concerned with road users (i.e., drivers, pedestrians, or cyclists) and provides them with knowledge, skills and attitudes related to safe driving. Enforcement changes aggressive behavior by road users by imposing penalties if they do not comply with traffic rules. Engineering involves both vehicle and road engineering. It is also argued that encouragement should be listed as the fourth “E.” This concept refers to techniques of behavior management designed to elicit safer road user behavior through modifying its consequences. However, it is hard to achieve this “zero accidents and no injuries” ideal because various components interact in road traffic systems. It is widely agreed that road traffic systems are composed of humans, vehicles and roads as well as driving contexts (e.g., traffic volume, weather condition, and time of day). Thus, a traffic accident may be considered as a system failure. The relative contributions of the components to accidents were clearly analyzed in studies (Sabey 1980; Treat 1980) showing that road conditions caused 28–34 % of traffic accidents, human error caused 93–94 %, and vehicle factors caused 8–12 %.

According to the National Police Agency of Japan (NPA 2007), the number of traffic fatalities of primary parties due to “distracted driving” and “looking aside while driving” has decreased at a very slow pace in recent years. This is also true for the numbers due to “failure to confirm safety factors (e.g., failure to stop before the “Stop” sign)” and “improper steering/braking” (Fig. 10.1). To reduce the number of traffic accidents, it seems important to assist drivers by providing them with proper information.

To improve traffic safety, the Japanese Ministry of Land, Infrastructure and Transport (MLIT) has actively promoted the development and application of advanced technologies such as Advanced Cruise-Assist Highway Systems (AHS) (MLIT 2007). One of the key AHS technologies is the in-vehicle traffic warning information (IVTWI) system, whose effects on traffic safety are not yet clear. One of the main reasons for this is that driving behavior has not been satisfactorily represented in research literature. When information is provided to people, it may not be retained for long in their memory. Several studies have demonstrated that even immediately after passing a sign to which they clearly responded, most drivers cannot recall what the sign was (Martens 2000; Milosevic and Gajic 1986; Shinar and Drory 1983). Psychologists have addressed this forgetting phenomenon, using two principal theories: time-related forgetting (Baddeley 1997; 1983; Henderson 1999) and interference-related forgetting (Lewandowsky et al. 2004). The former indicates that the information stored in human memory decays over time, whereas the latter means that old information in memory is displaced by new information. A wide range of interfering factors may cause people to forget information while performing a task.

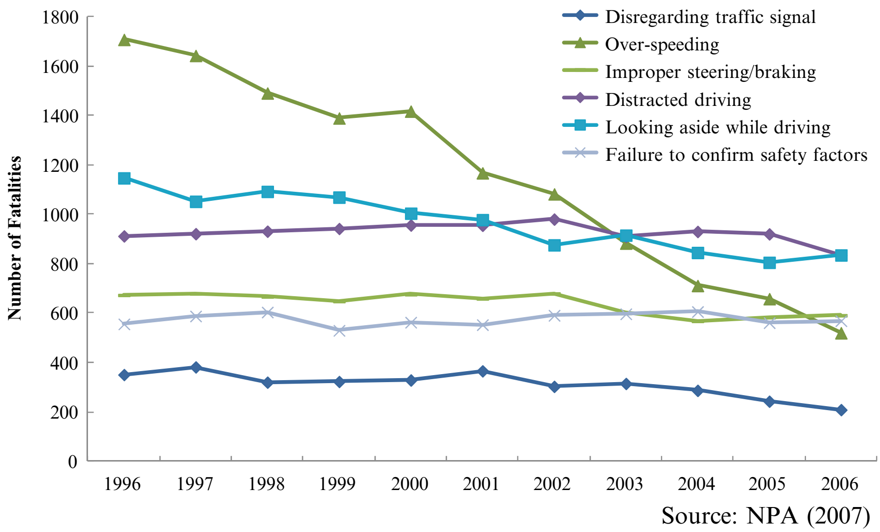

Fig. 10.1 Numbers of traffic fatalities of primary party by human errors. Source: NPA (2007)

The driver of a car receives information through multiple channels, such as driving environment, vehicles, and other drivers/passengers. However, it seems reasonable to suggest that if IVTWI could be provided at the right time and in the right format, the effects of interference might be minimized. For this reason, it is important to understand how drivers react to IVTWI while driving and how factors such as the timing and format of IVTWI provision influence this reaction. However, even the best existing analysis approaches adopt a dummy variable (i.e., one and zero) to indicate information provision while assuming that the effects of the information remain constant from the time it is provided. This is clearly unrealistic considering the forgetting phenomenon inherent in human short-term memory.

In this chapter, approaches to overcoming the limitations of existing studies are first developed, and drivers' responses to the IVTWI are examined by explicitly incorporating the influence of drivers' short-term memory, focusing on a signalized intersection with a limited signal visibility in Hiroshima City (see Fig. 10.2). The target intersection, named Hiranobashi-higashi intersection, is located on the national highway 'Route 2' in the central area of Hiroshima City, and it is close to a bridge and formed with a crest vertical alignment with the crest at 120 m from stop-line. Drivers more than 190 meters from the stop line on this approach usually have difficulty seeing traffic conditions in front. This makes this intersection one of the most dangerous on the national highway. Although a prewarning traffic signal is installed on the median strip, it has been reported as ineffective because it is too close to the traffic signal. The poor visibility has frequently caused rear-end collisions. This type of traffic accident is typical of those observed on Route 2, which, being located in the delta area of Hiroshima City, includes many river bridges.

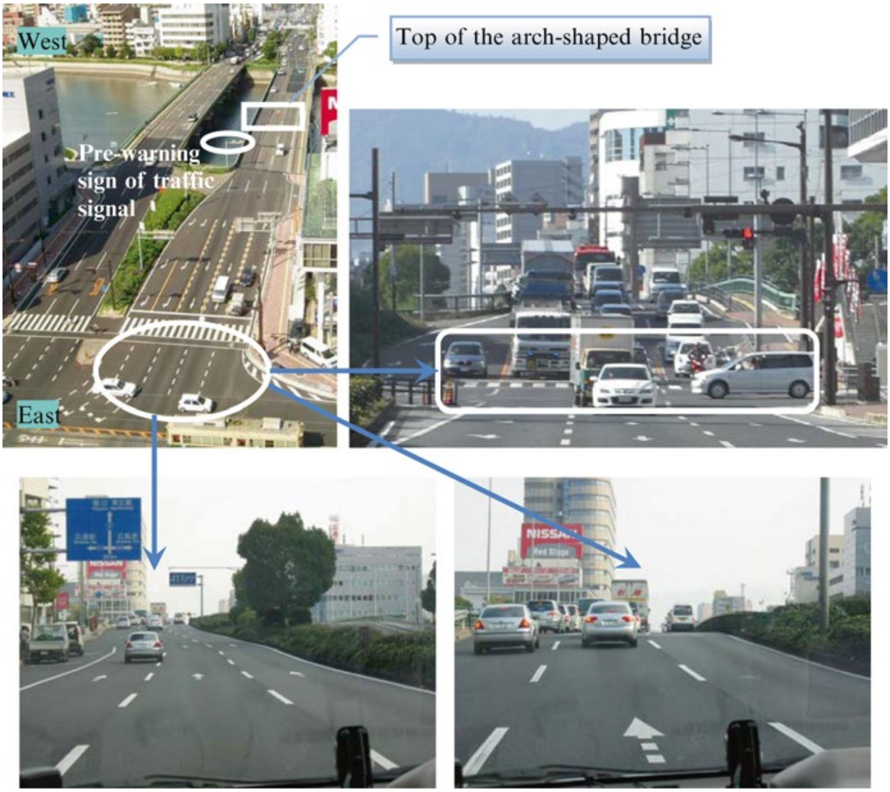

Fig. 10.2 Poor visibility nearby the Hiranobashi-Higashi intersection

10.2 Development of a Driving Risk Model

The common finding that an increase in speed deviation (i.e., the difference between a driver's speed and the average speed on a section of road) could increase the likelihood of an accident led us to adopt magnitude of speed deviation as an indicator of traffic safety. We therefore use the term *driving risk* to describe the level of road safety in terms of a driver's speed on a road section. In other words, greater homogeneity of speed increases safety (Lassarre 1986).

To define the level of *driving risk*, the unit of standard deviation is proposed because in most cases, it approximates the 85th percentile minus the average speed (TRB 1998, p. 42). Road segmentation is relevant when evaluating traffic safety. Two methods are generally suggested: the homogeneous-segment method (Kweon and Kockelman 2005) and the fixed-length method (Shankar et al. 1995). To control for geometric features rigorously, the former method has been the prevailing approach. In this approach, the roadway is first divided into sections according to the characteristics of vertical and horizontal alignment (e.g., horizontal curves and

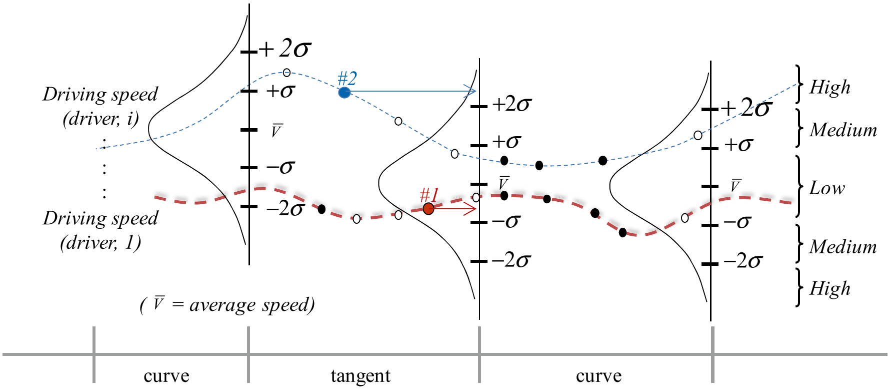

Fig. 10.3 Concept of driving risk measurement

radius and vertical grades), and the average speed and standard deviation are then computed for each section.

Figure 10.3 shows the concept of *driving risk*. The risk is reduced when individual driving speed falls within a range of one standard deviation on a road section; otherwise, it increases. For example, in the case of driver *i* (i.e., the dashed line in Fig. 10.3) traveling on the tangent of a roadway under study, the level of *driving risk* at points #1 and #2 can be evaluated as low and high, respectively.

By measuring the magnitude of speed deviation, it may be seen that the level of *driving risk* can be considered as a categorical variable showing that the danger of driving behavior will increase with larger values of y_n. To represent this variable, an ordered response probit (ORP) model is applicable. The ORP model can be constructed by defining the following latent variable. Here, sample *n* refers to the value of measured speed:

$$y_n = \begin{cases} 1, & \text{if } \Delta V_n \le \sigma & \rightarrow \text{Low driving risk} \\ 2, & \text{if } \sigma < \Delta V_n \le 2\sigma & \rightarrow \text{Medium driving risk} \\ 3, & \text{if } \Delta V_n > 2\sigma & \rightarrow \text{High driving risk} \end{cases} \tag{10.1}$$

$$\Delta V_n = \left| \bar{V} - V_n \right|$$

$$y_n^* = \beta' x_n + \varepsilon_n \tag{10.2}$$

where

y_n : level of *driving risk* of sample *n*,
V_n : driving speed of sample *n*,
$\bar{V}$: average speed on a road section under study,
ΔV_n: speed deviation between $\bar{V}$ and V_n,
σ : standard deviation,
y_n^* : latent variable capturing the *driving risk* of sample *n*,

x_n : vector of explanatory variables,
β : vector of parameters to be estimated, and
ε_n : error term assumed to follow a standard normal distribution.

10.3 Influence of Forgetting on Human Decisions

As Fuller and Santos (2002) stated, human memory can be divided into two parts: short-term and long-term memory. Long-term memory is more closely related to driving skills through habits formed by repetition over a long period of time (Shinar 2007). Drivers also use short-term memory in driving situations. Since short-term memory was first defined by Locke in the 17th century (Logie 1996), many researchers have found that its capacity is limited (Ebbinghaus 1885/2012; Miller 1956), that information in the short-term memory decreases over time (Lay 1986; Peterson and Peterson 1959) and that it will fade (or will be replaced) if another task is interposed (Cumming 1964). For example, Ogden (1995) mentioned that details of most features such as signs, signals, pavement markings, other vehicles, and pedestrians that a driver encounters on a trip, are merely "noted," and after use (if any) is made of the information, it fades from memory, without entering the long-term memory. This suggests that information stored in a driver's short-term memory declines because of the lapse of time and interference.

However, most existing studies of traffic warning information have introduced a dummy variable, with a value of one representing information provision and zero meaning no information is provided. The value of one implicitly suggests that the utility of the information provided to a driver remains constant. This would mean that the timing of information provision is irrelevant. However, the more time there is between information provision and the moment a driver needs to react to it, the more likely the information is to fade from the driver's memory. Because short-term memory is likely to lose information over time, the above "general rule" might be unrealistic. To measure the influence of traffic information properly, it is necessary to examine how the information provided decays in a driver's memory while he/she is driving. In real driving situations, sources of interference are manifold, and IVTWI provision should be timely. Therefore, IVTWI stored in short-term memory may fade rapidly because of various sources of interference during driving. Reflecting knowledge from previous studies in both transportation and other fields, especially psychology, this study assumes that the utility of IVTWI should be positive and that it will gradually decrease to zero, indicating that the information is completely forgotten or no longer useful. Thus, the following three assumptions related to the utility of IVTWI can be made.

(Assumption A) The utility of IVTWI is generated at the time of provision.
(Assumption B) The utility of IVTWI decreases over time after provision.
(Assumption C) The minimum utility of IVTWI is zero.

The forgetting curve in human memory was first generated by Ebbinghaus (1885/2012). Rubin and Wenzel (1996) recently examined the regularity of forgetting with a two-parameter function investigating the possibility of using one retention function to describe memory. They presented five functions—a linear, an exponential, a logarithmic, a power, and a hyperbolic function—to describe the regularity of forgetting. In the present study, the hyperbolic function is excluded because it has been found to be mostly useful for measuring animal memory (Harnett et al. 1984; Staddon 1983). The simplest form of function is the linear function. However, its drawback is that in an actual curve-fitting procedure, negative values of M (for large values of t) never occur. The exponential function has a simple form; its effectiveness has been confirmed in many short-term memory experiments, and consequently it has been widely applied to describe short-term memory (Peterson and Peterson 1959; Wickelgren 1970; Dosher and Ma 1998). The use of a logarithmic function was supported by early studies (e.g., Luh 1992; Woodworth 1938; Crovitz and Shiffman 1974). Like the linear function, the logarithmic function has the limitation that a negative value for the amount of memory U can be observed when t exceeds a certain value. Moreover, when $t = 0$, the logarithmic function cannot be defined. Finally, the power function was proposed and validated by Wickelgren (1974, 1975a, b), Wixted and Ebbesen (1991), and Sikström (2002); however, its most serious drawback is that it cannot be defined when time $t = 0$.

Providing IVTWI through a navigation system may become ineffective when a driver cannot interpret the information quickly or take action in response. Furthermore, during and after IVTWI provision, drivers must process other information concurrently because of interference (e.g., information related to driving, vehicle controls and unrelated thoughts). Hence, forgetting commences soon after the IVTWI is provided.

Figure 10.4 illustrates a driving situation with IVTWI provision, considering event-related interference and with constant strength of information.[1] In this case, a driver receives the information from 8 to 20 s after a predefined reference time (0), meaning that the exposure to IVTWI is for 12 s. Traditionally, a dummy variable is adopted to distinguish between cases with and without information, using "1" to represent a case "with information" and "0" for one "without information." This assumes that before IVTWI exposure, the utility of information is zero, and that it reaches its maximum at the start of exposure and continues at the same level to infinity (Fig. 10.4). However, given the influence of short-term memory, this assumption is not realistic, and the utility function should be defined so that it decays over time.

The four forgetting functions mentioned above have been validated using only data from small-scale laboratory experiments conducted by psychologists. To apply them to the case of IVTWI, some modifications may be required. In addition, it is necessary to discover the most suitable form of the function for reflecting the influence of short-term memory on driving, as illustrated in Fig. 10.4. To do this, we modify the function as shown in Eqs. (10.3)–(10.6), by adding a dummy variable ρ and a new term t_0. The variable ρ is used to indicate the state of information provision, and it equals 1 "after information provision" and 0 "before information provision." The elapsed time

[1] For example, when a driver receives two types of information, voice and image, with same content, the retention time of the information might be different because the strength of information is different.

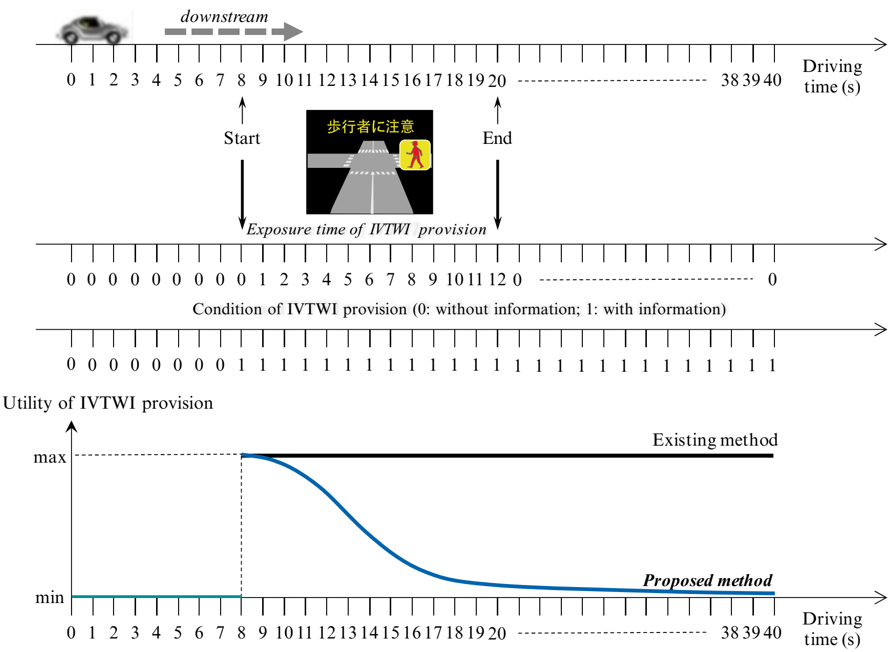

Fig. 10.4 Illustration of IVTWI provision and hypothetical utilities

t is further divided into two parts: driving time *t* and initial time of IVTWI exposure t_0, where t_0 is included in *t*:

$$U(t) = (-m \cdot (t - t_0) + b) \cdot \rho : \text{linear function} \tag{10.3}$$

$$U(t) = (b \cdot e^{-m \cdot (t - t_0)}) \cdot \rho : \text{exponential function} \tag{10.4}$$

$$U(t) = (b - m \cdot ln(t - t_0)) \cdot \rho : \text{logarithmic function} \tag{10.5}$$

$$U(t) = (b \cdot (t - t_0)^{-m}) \cdot \rho : \text{power function} \tag{10.6}$$

where

$U(t)$: utility of information usage (i.e., in psychology, the amount of memory),
m : forgetting rate,
b : intercept to represent strength of information, and
t : elapsed time.

Of the above four functions, the exponential function is the most appropriate form for describing the utility that a driver derives from using the IVTWI, reflecting the forgetting phenomenon in short-term memory shown in the above three assumptions (A, B and C). Having clarified the form of the function describing the utility of IVTWI, the effects of IVTWI on driving behavior will be evaluated. However, first the data used in this study are described briefly.

10.4 On-site Driving Experiment: In-vehicle Traffic Warning Information Provision

To examine the effects of IVTWI provision, we conducted an on-site driving experiment (also called a probe vehicle experiment) from November 21 (Tuesday) to 27 (Monday), 2006, targeting the signalized intersection shown in Fig. 10.1. Fourteen young drivers (one female and 13 male students from a local university) were recruited. All were in their early twenties (an average of 22.5 years of age with a standard deviation of 1.7 years), and 86 % had driven in the study area only once before, and 64 % had less than 3 years of driving experience. The experiment was conducted every day from 9:00 a.m. to 5:00 p.m., avoiding morning and evening peaks to remove bias due to external factors, such as excessive congestion or low speed. Table 10.1 shows the weather conditions during the experiment.

Four types of IVTWI were tested: static and dynamic voice-based information, and static and dynamic voice and image-based information (see Fig. 10.5), provided at one of two times (210 and 300 meters before the stop line). A "no information" scenario was also included. The information types and timings were combined and shown to drivers randomly. When stopping vehicles were detected in the surveillance area (i.e., between the crest and the stop line), the information "Attention, stopping vehicles ahead!" was announced via the navigation system (called dynamic information). If the surveillance area was free from stopping vehicles, the information "Attention, traffic signal ahead!" was provided (called static information). The static information did not mean that the signal had changed but was a simple warning to alert

Table 10.1 Weather conditions during the on-site driving experiment

Date	11/21	11/22	11/23	11/24	11/25	11/26	11/27
Day	Tue	Wed	Thu	Fri	Sat	Sun	Mon
Weather condition	Clouds, Rain	Sunny	Clouds	Sunny	Sunny	Rain	Clouds, Rain

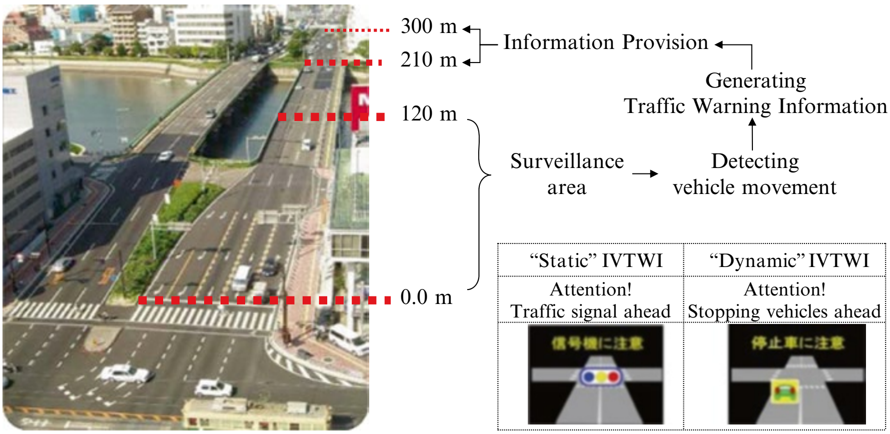

Fig. 10.5 Study area of the first on-site driving experiment

(i) Probe vehicle (ii) HUD image

Fig. 10.6 Apparatus used in the first on-site driving experiment. (i) Probe vehicle, (ii) HUD image

the driver to the signal. Stopping vehicles were detected in real time by an experimenter observing the intersection from the window of a room on the 11^{th} floor of a high-rise building near the intersection, from which position vehicles could be clearly identified. The experimenter was in direct contact with another experimenter, who controlled the IVTWI provision from the rear seat of the probe vehicle. Once the IVTWI was triggered, the information was displayed until the driver crossed the stop line. Because exposure time changed with driving speed, the average exposure to the IVTWI was 21.38 s. Before the experiment, drivers were instructed to drive the probe vehicle along the designated route as usual. They knew that they would receive traffic information from the navigation system inside the vehicle, but they did not know when or what kind of information would be provided.

Figure 10.6 shows the probe vehicle used for the on-site driving experiment. The probe vehicle in this study was developed by the National Institute for Land and Infrastructure Management in Japan. A Global Positioning System (GPS) sensor equipped in the probe vehicle automatically recorded the location, driving speed, acceleration and deceleration every 0.1 s. Other driving metrics, such as lateral acceleration, gap distance (distance from other vehicles), braking pressure and handling were measured using built-in sensors on the vehicle. Information was provided to drivers via the voice- and/or image-based human–machine interface (HMI). The IVTWI images were shown through a heads-up display (HUD) on the windshield, superimposing the information on the driver's view of the road environment.

10.5 Model Specification, Estimation, and Effects of Information Provision

10.5.1 Utility Function with Short-Term Memory

To clarify the effects of IVTWI provision and other factors on traffic safety, the *driving risk* model with an ORP structure (Eqs. (10.1) and (10.2)) was applied. For comparison, two types of ORP models were estimated. One model only had a

Table 10.2 Variables used for model estimation

Variables	Definition	Mean	S.D.
Traffic flow factors			
Speed change	The absolute value of the difference between speed at time t and that at t-1 (the time interval is 0.1s in this study) [km/h]	0.169	0.251
Gap distance	The distance between the rear end of preceded vehicle and the front end of the probe vehicle, divided by 1000 [m]	0.104	0.034
Geometry factors			
Signal visibility	The ability of a driver to identify traffic signal due to obstacles [0 = visible (over 190 m from the stop-line); 1 = invisible]	0.351	0.477
Vertical grade	The absolute value of vertical grade divided by 10 [%, positive sign = upgrade; negative sign = downgrade]	0.285	0.199
Environment factors			
Road surface	The condition of road surface when driving was performed on the subject road [0 = dry; 1 = wet]	0.432	0.495
Time slot	The time of day implementing the driving experiment during a day [0 = morning; 1 = afternoon]	0.491	0.500
Day slot	The day of recording the scene either weekday or weekend [0 = weekday; 1 = weekend (holiday)]	0.589	0.492
Driver factors			
Trial number	The number of driving trials on the subject road during a day divided by 10 [integer, positive sign]	0.300	0.135
Driving experience	The real driving experience (i.e., months) of each driver divided by 10 [integer, positive sign]	0.196	0.108
Provision of the in-vehicle traffic warning information (IVTWI)			
Provision of IVTWI	Whether the IVTWI is provide or not [0 = without information; 1 = with information]	0.659	0.474

dummy variable to indicate that IVTWI was provided, which was set to one if information was provided and zero otherwise. This model is called "the existing model." Another model, called "the proposed model," was constructed based on the exponential form in Eq. (10.4). In line with the studies by Dosher and Ma (1998) and Wickelgren (1970), the distribution of forgetting over time shown in Eq. (10.4) was modified for application to real driving situations, based on the assumption of a Gaussian distribution with mean 0 and standard deviation σ_t, where σ_t indicates the strength of the forgetting curve to be estimated:

$$U(t) = \begin{cases} \dfrac{1}{\sigma_t\sqrt{2\pi}}\exp\left(-\dfrac{(t-t_0)^2}{2\sigma_t^2}\right) & \text{if } t \geq t_0 \\ 0 & \text{if } t < t_0 \end{cases} \tag{10.7}$$

where the other notations are as described in Eq. (10.4).

To estimate the *driving risk* models, the independent variables shown in Table 10.2 are adopted, and five major types of factors are included: traffic flow factors, geometric factors, environmental factors, driver factors, and provision of IVTWI. The effectiveness of both the existing and proposed models is confirmed. It is also clear that the proposed model is superior to the existing model. For details, refer to Kim et al. (2010).

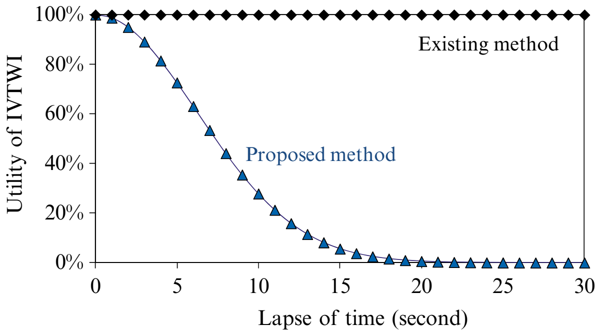

Fig. 10.7 Estimated utilities of IVTWI between the existing and proposed models

10.5.2 Effects of In-vehicle Traffic Warning Information Provision

The parameter for IVTWI provision has a positive value in the existing model, meaning that IVTWI provision increases *driving risk*. In the proposed model, however, the corresponding parameter has a negative value, suggesting that the provision of IVTWI is effective in reducing *driving risk*. Because the proposed model has a logical structure and is more accurate than the existing model, it appears most likely that *driving risk* could be reduced by providing IVTWI.

Figure 10.7 shows the estimated utility functions of IVTWI in the proposed model and the influence of IVTWI provision in the existing model. In the case of the existing model with a dummy variable, the influence of provision is constant over time. As stated above, this ignores the forgetting phenomenon. On the other hand, the estimated utility function of the proposed model can describe the three assumptions (A, B and C) related to the characteristics of short-term memory. Specifically, utility begins immediately when IVTWI is provided. The utility monotonically decreases for nearly 20 s, when it approximates the value of zero. This propensity for a decaying curve captures forgetting in the driver's short-term memory. In addition, Fig. 10.7 shows that the elapsed time (almost 7.5 s after provision) that corresponds to 50 % of utility of IVTWI (i.e., on the y-axis) is considerable because the uncertainty of the information provided becomes maximal at that point. Uncertainty about the IVTWI is maximized where the driver can visually confirm the traffic situation in the surveillance area; that is, 190 meters from the stop line. Based on the speed analysis of the collected data, within 7.5 s, a driver can move nearly 105 meters when traveling at an average speed of 50 km/h. In other words, to maximize the influence of IVTWI on driving behavior and traffic safety, information should be provided at least 295 m (= 190 m + 105 m) before the stop line to minimize loss.

The probability of changes in *driving risk* because of changes in IVTWI utility is also interesting. To address this concern, a sensitivity analysis was performed by controlling the variable of IVTWI provision, using a value of zero for discontinuous variables and average values for continuous variables. Figure 10.8 shows the impacts of

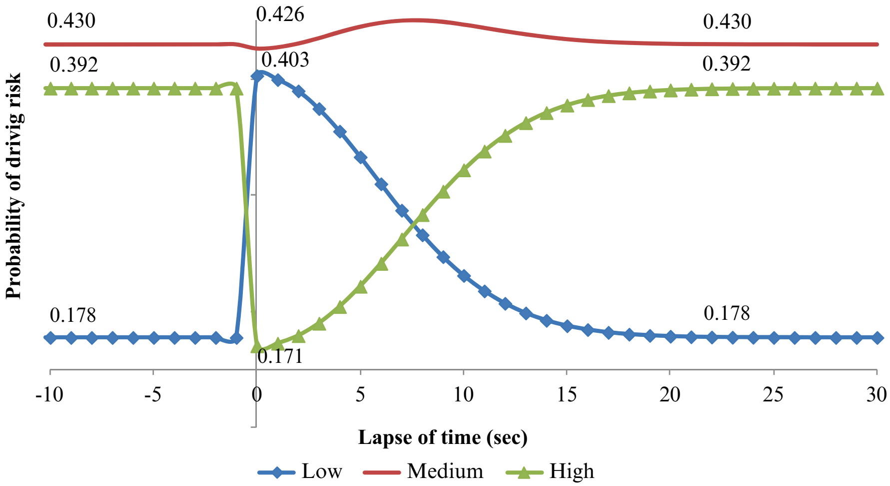

Fig. 10.8 Probability changes in driving risk with IVTWI provision over time

IVTWI provision on changes in probability of low, medium, and high *driving risk*. When no IVTWI was provided (i.e., negative values on the x-axis), the probabilities of low, medium, and high *driving risks* were 0.178, 0.430, and 0.392, respectively. At the instant that IVTWI was provided to drivers (i.e., 0 on the x-axis), these probabilities changed to 0.403 (126.40 % increase), 0.426 (0.93 % decrease), and 0.171 (56.38 % decrease), respectively. These probabilities vary for nearly 20 s, after which they return to the initial condition when no IVTWI was provided. This tendency reconfirms our assumption that the utility of IVTWI is reduced over time. In addition, Fig. 10.8 shows that the impacts of IVTWI provision changed from positive to negative at 7.5 s after provision, showing the same probabilities for low and high risk, and a maximum value for medium risk. After that, the medium risk began to decrease, the low risk continuously decreased, and the high risk further increased until the initial state of *driving risk* (i.e., the "without provision" condition) was reached again.

10.5.3 Comparison with Other Factors

Regarding other variables, it was found that increasing the values for gap distance and vertical grades on wet road surfaces decreases *driving risk*. This finding is consistent with several other studies (e.g., Saad 1996; Haglund and Åberg 2002; Andrey and Kanpper 2003). Other estimated parameters confirm our prior belief that the average *driving risk* has a negative relationship with variables such as speed change, signal visibility, time slot, trial number, and driving experience. For example, the effects of speed changes are similar to the road design consistency indicator used by Cafiso et al. (2005), which is that a larger change of speed

Table 10.3 Elasticity of continuous variables

Continuous variables	*Driving risk* Low	Medium	High
1 % increase in speed change	–0.080	0.005	0.088
1 % increase in gap distance	0.766	–0.048	–0.848
1 % increase in vertical grades	0.468	–0.030	–0.517
1 % increase in trial number	–0.888	0.056	0.982
1 % increase in driving experience	–0.365	0.023	0.404
1 % increase in utility of IVTWI	0.470	–0.030	–0.519

indicates reduced traffic safety. It is also revealed that *driving risk* increases on the road section with limited visibility. In addition, the effects of time slot, trial number, and driving experience on *driving risk* are consistent with earlier studies focusing on the relationship between the characteristics of young male drivers and traffic safety (Masten 2004; Corbett 2003; Yagil 1998; Maycock 1995; Leger 1994; Finn 1986). These studies indicated that *driving risk* could increase if male drivers in their early twenties with less than 2 years of driving experience drove in the afternoon in a one-day repeated driving scenario.

The relative magnitudes of the estimated coefficients are also of interest. Because *driving risk* is specified as a linear function of the explanatory variables, the relative magnitudes of the estimated coefficients of the discontinuous variables are, in most cases, a measure of the relative impacts of those variables on the average *driving risk*. For instance, the estimated coefficient of the discontinuous variable recording signal visibility (= 0.412) is about 2.03 times higher than that of time slot (= 0.203). This indicates that the increase in *driving risk* faced by an individual driving on a road section with limited signal visibility is about 2.03 times higher than that of driving in the afternoon, assuming that all other factors are equal. Most of the estimated coefficients of discontinuous variables can be compared in this way, and their relative influences on average *driving risk* can be ranked.

The comparison of continuous variables is also important. Table 10.3 presents the elasticity results of the variables, showing that all estimates (absolute values) are significantly less than one. This means that changes in any continuous variable lead to small changes in *driving risk*. For example, a 1 % increase in gap distance, vertical grade, or IVTWI utility results in a decreased probability of medium and high risk and an increased probability of low risk. Although the effect of an increased IVTWI utility is smaller than that of increased gap distance, it is of the same magnitude as the effect of increased vertical grade. The results show that provision of IVTWI is effective in reducing *driving risk*.

10.5.4 Effective Ways to Provide the In-vehicle Traffic Warning Information

According to the experimental scenarios, four types of IVTWI were tested; i.e., static and dynamic voice-based information, and static and dynamic voice and image-based information at two different timings of provision (i.e., the different locations of information provision). To assess the effects of these four IVTWI formats on *driving risk* at different locations, we additionally estimated five *driving risk* models. The first model is used to evaluate the influence of location of IVTWI provision (210 m and 300 m from the stop line) on *driving risk*. The other four models are used to evaluate the influences of various information formats (i.e., static or dynamic, voice, or voice and image) at both locations. The first model shows that provision of IVTWI at 300 m from the stop line contributed more to reducing *driving risk* than at 210 m. This suggests that earlier provision of information allows drivers more time to make a safe driving decision before approaching the road section with limited visibility. Furthermore, the other four models demonstrate that drivers preferred the voice-based provision 210 m from the stop line. In contrast, at 300 m, drivers preferred the IVTWI with voice and image. Concerning information type, dynamic information was preferred to static information at both locations.

10.6 Effects of Information Under Heterogeneous Driving Situations

10.6.1 Driving Behavior Under Different Driving Situations

For safety, drivers have to take appropriate action in response to different situations in which the phenomenon of forgetting may arise. Two types of driving situations can be distinguished: the interactive and free-driving situations. In the former situation, a driver must follow another vehicle(s), and in the latter, he/she can drive at his/her own speed. In the free-driving situation, the driver can choose a speed without interference by other vehicles. In contrast, in the interactive-driving situation, the driver must pay sufficient attention at least to the vehicle in front. In this sense, the driver is required to perform more complicated tasks in the interactive situation than in the free-driving situation. Accordingly, under these two heterogeneous situations, it is expected that the roles and effects of IVTWI provision will differ. Because a driver's short-term memory is limited, an additional task while driving may significantly weaken the effects of IVTWI, and such deteriorated effects of information could be more noticeable in the interactive-driving situation than in the free-driving situation. The above psychological explanation suggests that the effects of the information depend on the traffic situation. To evaluate the effects of information on traffic safety properly, the forgetting phenomenon in drivers' short-term memory, especially in heterogeneous traffic situations, must be taken into account.

10.6.2 Data Processing for Analysis

The same data collected in the previous section are used here. Following data retrieval, the 4,836 samples collected are divided into 1,746 samples for the interactive-driving situation and 3,090 for the free-driving situation. Note that a sample means the value for driving speed detected by the probe vehicle every 0.1 s. Because the detection points vary according to speed, different numbers of samples were obtained for each run. If driving speeds were always exactly 60 km/h, for example, the sample size should be 4,320 (= 24 runs × 180 detection points (= 300 m ÷ 16.67 m/s ÷ 0.1 s) along the whole road). However, because driving speed varied across road sections and between runs, the sample size for this study is 4,836. During the on-site driving experiment, two traffic operation factors (speed change and gap distance), two geometry factors (signal visibility and vertical grade), and three environmental factors (road surface, time slot, and day) were observed.

10.6.3 Heterogeneous Effects of Information Provision

1. Specification of Driving Risk Models
   The purpose of this part of the analysis is to investigate how to provide the IVTWI. Specifically, timing, information type (static or dynamic), and human–machine interface (voice or voice and image) will be examined. The utility function reflecting the influence of forgetting is defined in Eq. (10.7), as in the previous section. Two *driving risk* models are estimated: Model 1 and Model 2. Model 1 is used to evaluate the influence of provision timing (i.e., provision locations: 210 m and 300 m from the stop line) on *driving risk*. Model 2 is used to evaluate the impacts of information type (static or dynamic) and human–machine interface (voice or voice and image) at two locations where it is provided. In addition to these information-related variables, variables related to traffic operation, road environment and geometry, and driver characteristics are simultaneously introduced into the *driving risk* models. The samples from the case of no information were excluded.
2. Heterogeneous Effects of IVTWI Provision in Different Driving Situations
   This study assumes that the safety impacts of IVTWI provision may vary over time in the two heterogeneous driving situations. Figure 10.9 confirms this assumption. Specifically, the estimated utility functions approach zero (0.001) at about 17 s in the interactive-driving situation and 20 s in the free-driving situation after providing IVTWI. This indicates that the decay of utility of IVTWI in the interactive-driving situation is faster than that in the free-driving situation. This may be because drivers must perceive and react to more sources of information simultaneously in an interactive-driving situation than in a free-driving situation.

   Regarding the safety impact of IVTWI provision timing, it is shown that drivers prefer to receive IVTWI at 300 m from the stop line rather than at 210 m, which is observed in both heterogeneous traffic situations. This emphasizes that for effective reduction of *driving risk*, the IVTWI should be provided before drivers approach the crest (at 120 m from the stop line) so that they can take proper evasive action.

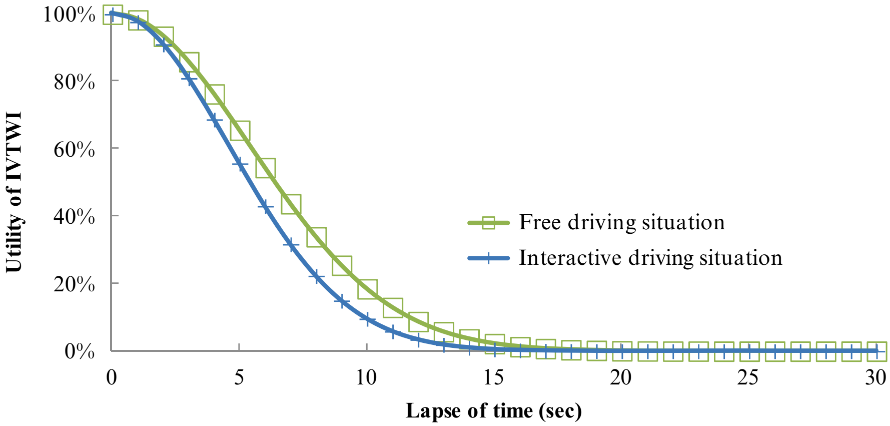

Fig. 10.9 Estimated IVTWI utility functions in heterogeneous traffic situations

The information and human–machine interface types of IVTWI have different effects on *driving risk* according to provision timing. In the interactive-driving situation, dynamic voice-based information is preferred by drivers at 210 m from the stop line, and dynamic voice and image-based information is preferred at 300 m. In contrast, in the free-driving situation, static voice and image-based information is preferred at both 210 m and 300 m.

To examine the safety impacts of IVTWI provision methods in detail (i.e., provision timing, and types of information and human–machine interface) on *driving risk*, a sensitivity analysis was conducted. For this analysis, the concept of "Standard *Driving Risk* Model (SDRM)" is used to represent a standard driving condition, where all variables have their average values. Note that the average value of the IVTWI utility was endogenously estimated from the empirical data.

Figure 10.10 shows that the probability change of *driving risk* is affected by the method of information provision in the two traffic situations. Figure 10.10 (i) shows the probability change of *driving risk* in the interactive-driving situation. In the case without information, the *driving risk* probabilities for low, medium, and high risk are 0.127, 0.634, and 0.239, respectively. These probabilities change to 0.260 (low), 0.626 (medium), and 0.114 (high) when IVTWI is provided. Such changes are also affected by the timing of information provision. For example, when the IVTWI is provided at 210 m, the probabilities become 0.186 (low), 0.471 (medium), and 0.343 (high), and change to 0.251 (low), 0.483 (medium), and 0.266 (high) when the information is provided at 300 m from the stop line. In addition, the *driving risk* probabilities change with the information and human–machine interface types. For example, when the dynamic voice-based information is provided at 210 m, the probabilities change to 0.146 (low), 0.597 (medium), and 0.257 (high), and to 0.144 (low), 0.596 (medium), and 0.261 (high) when dynamic voice and image-based information is provided at 300 m. Similarly, these changes of *driving risk* are seen in the free-driving situation,

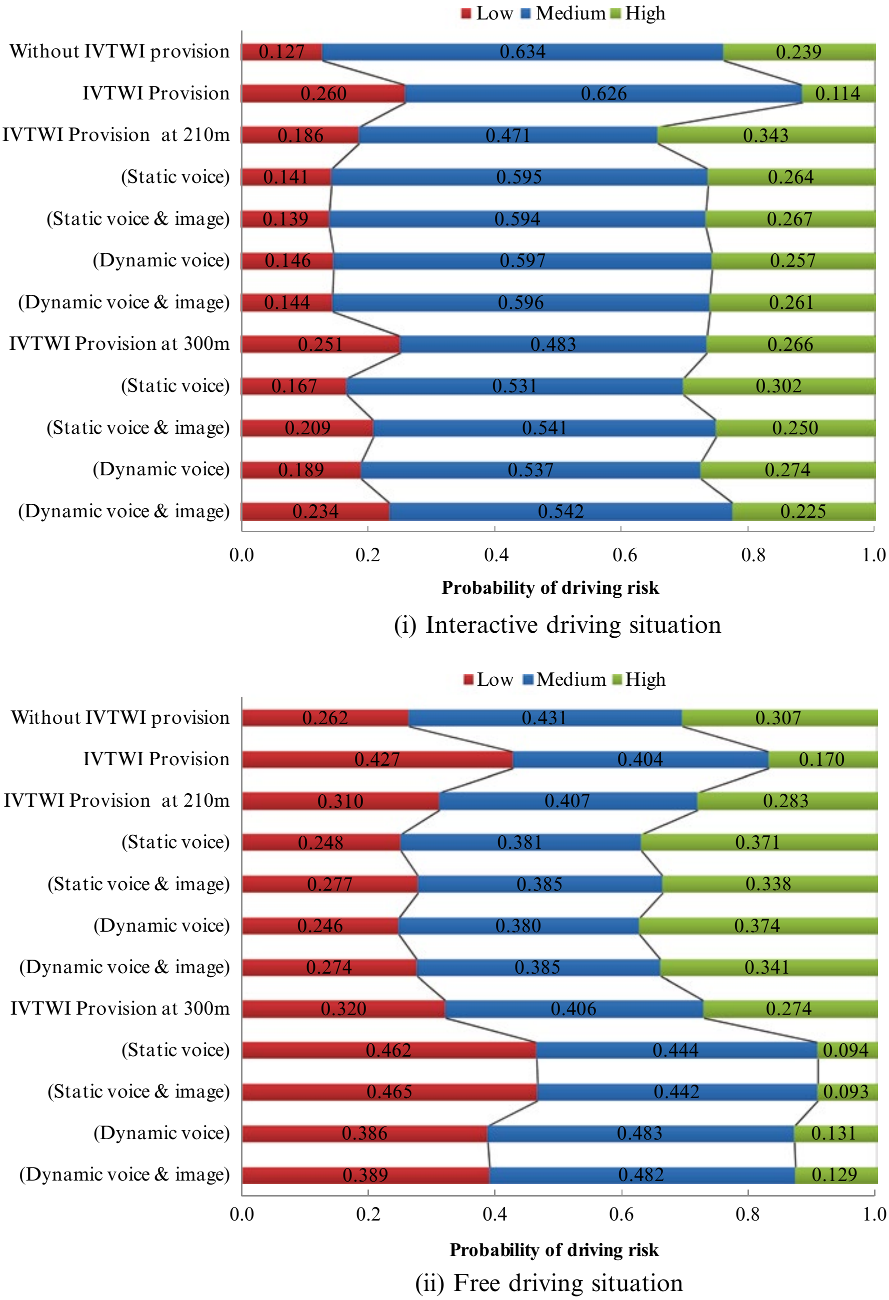

Fig. 10.10 Probability change in driving risk (SDRM condition). (i) Interactive driving situation. (ii) Free driving situation

depending on the information and human–machine interface types under different timings of provision. Figure 10.10 (ii) shows that *driving risk* probabilities in the case without information are 0.262 (low), 0.431 (medium), and 0.307 (high). These values change to 0.427 (low), 0.404 (medium), and 0.170 (high) when the IVTWI is provided. Regarding the impacts of provision location, the same tendency in probability changes is observed in the interactive-driving situation. For example, when the IVTWI is provided at 300 m, the improvement in *driving risk* is greater than that at 210 m in the sense that the probabilities change from 0.310 (low), 0.407 (medium), and 0.283 (high) to 0.320 (low), 0.406 (medium), and 0.274 (high), respectively. These probabilities also vary with information and human–machine interface types. For example, static voice and image-based information is preferred when information is provided at 210 m and 300 m, because the *driving risk* probabilities change from 0.277 (low), 0.385 (medium), and 0.338 (high) to 0.465 (low), 0.442 (medium), and 0.093 (high), respectively.

10.7 Influence of Driving Experience on Information Provision

Experienced drivers are generally expected to take more appropriate action than inexperienced drivers. This expectation has been justified in the studies by Patten et al. (2006) for a peripheral target detection task inside a vehicle and by Shinar et al. (1998) for a test of road sign detection. However, it is questionable whether driving experience has a positive influence on traffic safety for young male drivers (20–29 years old). This is because they have distinctive driving behavior, such as driving faster, decelerating and accelerating more abruptly, being less likely to come to a full stop at stop signs, and being more likely to tailgate other cars than middle-aged (30–64 years old) and older (65+ years old) drivers (Porter and Whitton 2002).

To assess the influence of information provision and driving experience, ex ante and ex post analysis using a dummy variable has been used in previous studies without consideration of human factors, especially drivers' memory. Because traffic safety depends a great deal on drivers themselves, it is essential to account for memory when evaluating traffic safety. Drivers can use as much of the information provided as possible within the capacity of short-term memory. Thus, it is a reasonable hypothesis that the utility of IVTWI changes over time and is affected by driving experience. Therefore, this study will examine this point, particularly by addressing human factors on the basis that the usability of the information provided depends on drivers' short-term memory as well as driving experience.

As shown in Fig. 10.11, in a driving exercise, drivers usually receive several stimuli (e.g., IVTWI and traffic signs) through receptors, perceive and identify these stimuli, and decide on responses within the capacity of their short-term memory. Moreover, this mechanism works according to the forgetting phenomenon, implying that drivers cannot remember all the given information over time. This property of short-term memory is also affected by driving experience.

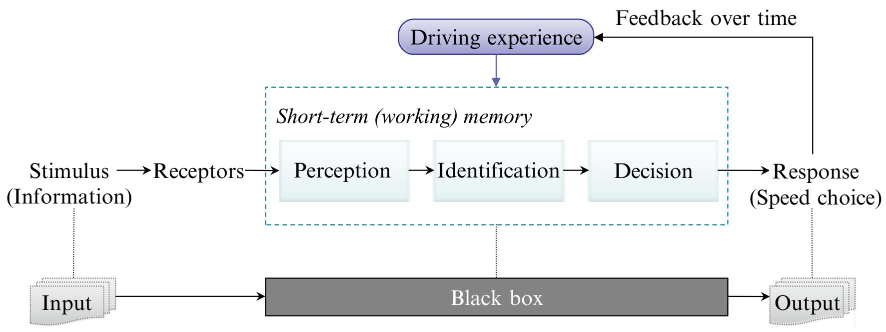

Fig. 10.11 Information process incorporating driving experience

10.7.1 Improving Utility Function and Model Estimation

As argued previously, time-related forgetting in the short-term memory is affected by driving experience. By adding a term for driving experience (DE) to Eq. (10.7), the utility of IVTWI incorporating driving experience can be expressed as follows, where the other notations are the same as described in Eq. (10.7):

$$U(t) = \begin{cases} [\frac{1}{v\sqrt{2\pi}} \exp(-\frac{1}{2}\frac{(t-t_0)^2}{v^2}) + \exp(\gamma(x_{DE}))] & if\ t \geq t_0 \\ 0 & if\ t < t_0 \end{cases} \tag{10.8}$$

where x_{DE} indicates driving experience, and γ is an unknown parameter to be estimated.

To estimate the *driving risk* model based on the ORP modeling approach, explanatory variables shown in Table 10.2 are adopted. Here we only focus on examining the effects of traffic information on driving experience. For comparison, three ORP models are estimated. One ORP model only has a dummy variable to evaluate the effects of IVTWI, which is set to one for the case of information provision and zero for the case of no information. This is called "the existing model." The other two models employ the utility function of IVTWI to reflect the influence of drivers' short-term memory. These are called "the proposed models." The difference between proposed models I and II is that Model I does not incorporate the influence of driving experience (i.e., $exp(\gamma(x_{DE}))$ is excluded from Eq. (10.8)), while model II does ($exp(\gamma(x_{DE}))$ is included). For detailed estimation results, refer to Kim et al. (2009).

10.7.2 Invariant Effects of Information Provision

The existing model estimates the parameter of IVTWI provision to be positive and statistically significant. This means that IVTWI provision increases *driving risk*.

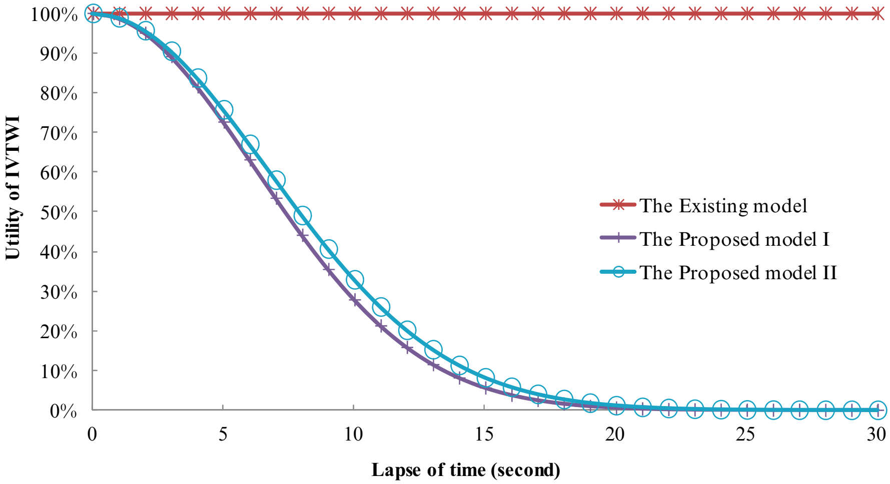

Fig. 10.12 Estimated utility functions of IVTWI in the existing and proposed models

However, in the two proposed models, it is observed that the parameters of the utility of IVTWI are negative, suggesting that IVTWI provision is effective in reducing *driving risk*. Because the proposed models showed greater accuracy than the existing model, it is believed that *driving risk* will be reduced by the provision of IVTWI.

Figure 10.12 compares the estimated utility functions of IVTWI from both the existing and proposed models. In the existing model, the use of a dummy variable implies that the influence of providing IVTWI remains constant over time. This obviously disregards the forgetting phenomenon in drivers' short-term memory. In contrast, the estimated utility functions from the proposed models demonstrate that (1) the maximum utility of IVTWI begins at the onset of provision, (2) the utility of IVTWI gradually decreases for nearly 20 s, and then (3) it approximates a value of zero, which represents minimum utility.

10.7.3 Prolonged Effects of Information Provision

When driving experience is included as an independent factor in short-term memory, it is found in the existing model and proposed model I that *driving risk* increases with the driving experience of a young male driver. However, the effects of driving experience on *driving risk* in the estimation results of proposed model II are different.

Focusing on the impacts of driving experience on the utility of IVTWI, Fig. 10.12 shows that the two utility curves of the proposed models have similar shapes and approach zero at almost the same point in time. Interestingly, the gradient of the estimated utility curve in proposed model II is less than that of proposed model I, but the difference is moderate. This means that drivers with more driving experience (i.e., experienced drivers) can remember the IVTWI provided for a longer time than inexperienced drivers. In other words, the decay of information in the short-term memory of inexperienced drivers is faster than in that of experienced drivers. From this result, we may infer that the likelihood of information loss by inexperienced drivers is higher than that by experienced drivers.

The estimated results also confirm this phenomenon because the absolute value of the parameter (−11.378) of the utility of IVTWI in proposed model II is greater than (−10.626) in proposed model I. This implies that providing IVTWI is more effective in reducing the *driving risk* of experienced drivers, compared with inexperienced drivers. This finding is consistent with the outcomes (e.g., increased driving control in experienced drivers) of earlier studies by Patten et al. (2006) and Shinar et al. (1998).

10.8 Conclusions

In a study of IVTWI, the timing of its provision and the human–machine interface (voice or voice and image), the time-varying utility of IVTWI was conceptualized to reflect explicitly the forgetting phenomenon that is typical of short-term memory. In a numerical analysis, it was found that an exponential function is the most appropriate form to describe this phenomenon. The effectiveness of the proposed approach—that is, incorporating the time-varying utility function into the ordered *driving risk* model—was confirmed by comparing the results with those from existing evaluation methods that simply rely on a dummy variable (0 = without information; 1 = with information).

Based on data collected from an on-site driving experiment conducted at a dangerous signalized intersection with limited signal visibility in Hiroshima City, Japan, the model estimation results showed that *driving risk* can be reduced by providing IVTWI, in that IVTWI utility gradually decreased for 20 s after the information was provided. However, the effectiveness of IVTWI utility was likely to remain for 7.5 s after provision. Reflecting the temporal change property in its utility, the effects of IVTWI provision on *driving risk* were further evaluated by comparing the results in two heterogeneous (i.e., interactive-driving and free-driving) traffic situations and incorporating the influence of long-term driving experience. It was found that in the interactive-driving situation, the decay of information provision was faster than in the free-driving situation. This indicates that the timing and human–machine interface of IVTWI provision should be considered according to the level of traffic congestion. Regarding the influence of driving experience on drivers' short-term memory, the results showed that greater driving experience enables drivers to memorize IVTWI better. Based on the results of this study, Table 10.4 summarizes the most effective format in which to provide IVTWI according to location and traffic situations. The overall summary is presented in Table 10.5.

Table 10.4 IVTWI provision ways considering provision location and traffic situation

Traffic congestion level	IVTWI provision at 210 m	IVTWI provision at 300 m
Not considered	Dynamic voice	Dynamic voice & image
Interacting traffic flow (less than 110 m of gap distance)	Dynamic voice & image	Dynamic voice & image
Free traffic flow (more than 110 m of gap distance)	Static voice & image	Static & voice

Table 10.5 Summary of a driving risk model with short-term memory

Driving risk model	Ordered-response probit model based on speed choice behavior
Applied human factors	The time-related forgetting phenomenon of short-term memory in various traffic situations, normal, interacting and free traffic flow, and with influence of driving experience
Used data	An on-site driving experiment
Subject	Young drivers (64 % are with less 3 year driving experience)
Site feature	Urban signalized intersection approach with a limited visibility
Countermeasure	Providing in-vehicle traffic safety warning information
Observed drivers' behavior	Non-stop speed choice behavior
Observed results	– Exponential function is the best for describing the time-based forgetting phenomenon – Goodness-of-fit the proposed model (utility of IVTWI applied) is better than that of the existing model (a dummy variable used) – IVTWI utility gradually decreased up to 20 s after providing the information under the experiment scenario – Effectiveness of IVTWI utility is likely to be kept for 7.5 s after provision under study – IVTWI provision could reduce the *driving risk* – Effects of IVTWI provision vary with driving situations – More driving experience enables drivers to better memorize the provided IVTWI – *Driving risk* decreases with increasing gap distance and vertical grades under wet road condition and decreases with increasing speed change, trial number, and driving experience in the afternoon when the visibility is limited
Limitations	– The effects of driving repetitions in on-site experiment have not been considered

10.9 Future Challenges

How can the level of traffic safety be assessed when there is a lack of traffic accident data? Under such circumstances, how can the effects of new countermeasures for traffic safety still be evaluated? What are the impacts of human factors on traffic safety? What alternative approaches could solve these issues? Such questions are common in the traffic safety field, but no convincing solutions have yet been suggested. In an effort to answer such questions, this chapter has attempted to clarify the effects of providing in-vehicle traffic warning information on traffic safety based on *driving risk* models with driving decision mechanisms, especially the influence of drivers' short-term memory and driving experience. Having shown the effectiveness of the proposed models and demonstrated the potential usefulness of in-vehicle traffic warning information, the limitations of the present study should be recognized. Some suggestions for future research are made with respect to three aspects: data collection, driver behavior modeling and application of human factors.

1. Data Collection
   By means of on-site observation, valid and reliable data can be collected; however, it may not be possible to capture the perceived risk of each driver. If drivers drive several times on the same roadway, the risks perceived by the driver may vary because the driver could become familiar with the road, vehicle and driving environment. This driving phenomenon has not been measured and reflected in the analysis. Measuring changes in perceived risk may be difficult but not impossible. As one measurement technique, for example, it is suggested that researchers monitor drivers' eye movements and capture time of fixation on the same stretch of road, which could then be compared over repeated visits. For this purpose, data collection is recommended on a road section before its opening to the public use or in a virtual reality driving simulator, because in actual driving situations, drivers respond to various contingent events that may complicate the measurement of changing perceived risk. Obviously, on-site driving experiments should be conducted with a variety of driver types, not just younger drivers, on different types of roads.
2. Driver Behavior Modeling
   Driver characteristics related to traffic safety may differ across individuals, because they differ regarding aspects such as experience, motives, trends, and lifestyles. In this sense, the versatile characteristics of subjects should be considered in order to avoid the ecological fallacy, even if only small numbers of drivers participate in the experiments. However, this point has not been considered in developing *driving risk* models. To address the issue of ecological fallacy effectively, the proposed *driving risk* models may be improved by applying fixed/random-effects modeling techniques. Another limitation related to driver behavior modeling relates to the change of driver behavior according to longitudinal and latitudinal span: the former represents driver behavior changes over locations (or time spans) and the latter indicates that driver behavior varies according to the number of traversals of the roadway. For a comprehensive understanding of dynamic changes in driver behavior, chronological analyses (e.g., time-series models and lag-distributed models) and/or Heckman's modeling practices are recommended.
3. Human Factors
   To evaluate the human factors in the influence of IVTWI on traffic safety, this study focused only on time-related forgetting in short-term memory based on the assumption that the strength of IVTWI scenarios—static and dynamic voice-based information, and static and dynamic voice and image-based information—would be the same.

This could limit the practicality of the findings of this research, because the assumption cannot entirely be supported regarding the forgetting features of memory simultaneously affected by various factors such as interference, experience, or strength of information. Nevertheless, overcoming this limitation may be outside the scope of traffic safety engineering. Rather, it may be a task for psychologists in the field of traffic safety. It is therefore recommended that researchers from related disciplines should be involved in interdisciplinary joint research. In addition, to consider the precise characteristics of information processing in traffic safety research, drivers' visual attention and perceived risk status should be elucidated, because information processing begins with visual attention and subjectively perceived risk. For this purpose, it is suggested that researchers capture visual attention using eye cameras and perceived risk through techniques such as questionnaires, group interviews and direct observation of driving behavior.

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Chapter 11
Uncertainty in Travel Behavior

Makoto Chikaraishi, Akimasa Fujiwara, and Junyi Zhang

Abstract This chapter gives an overview of uncertainty in travel behavior and its implications for transportation planning. We first address the issue of observation of travel behavior, which provides a foundation for analysis. We then focus on variations of travel behavior that contain information on uncertainties in terms of imperfect model fit to data. After that, changes in travel behavior are addressed, with regard to information on uncertainties in the degree to which the future will resemble the past. Based on the overview of behavioral observation, variations and changes, we discuss the avenues for future research on management of uncertainties from two viewpoints, one emphasizing the improvement of travel behavior analysis and the other the improvement of other components of the transportation planning process. From the former viewpoint, we show the importance of conducting uncertainty analysis to embed improved travel behavior analysis methods in the planning process in an appropriate manner. From the latter viewpoint, we underscore the importance of learning from accumulated experience in diverse countries/cities and learning from experience, particularly in developing countries.

Keywords Behavioral observations • Changes • Travel behavior • Uncertainty • Variations

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11.1 Introduction

11.1.1 Uncertainties in Transportation Planning

Transportation planning inevitably involves a number of uncertainties. For example, uncertainties exist in the prediction of travel demand, partly because the prediction is usually made with limited information. Even experts' value judgments involve uncertainties. For example, the value of reducing environmental impact has increased steadily, but the degree of change cannot be known precisely beforehand. Furthermore, we are unsure about how value will be judged in future. It is also difficult to prespecify all benefits and costs of a given project perfectly. Even if this were possible, there would be many unexpected events that affect the estimated benefits and costs, such as delay in construction schedules, political decisions regarding project finance, and lack of human resources to manage the project continuously.

Nevertheless, policy makers and planners must make decisions in the presence of uncertainties, resulting in a number of difficulties and complexities. When decisions are required under such circumstances, two extreme methods of managing uncertainty can be considered. The first method is to plan as if the decision maker understands and can predict the world precisely. Although this method has been widely applied in practice (Morgan and Henrion 1990), Gifford (2003) claims that "the central assumption that travel demand is predictable over a 20-year planning horizon is no longer supportable. Prediction-based analytical planning has been recognized as sharply inadequate". More problematically, because the estimated values are treated as if they were true despite the existence of uncertainties, planners and consultants could integrate political wishes into their forecasting framework, potentially causing implicit appraisal biases (Flyvbjerg et al. 2003) and consequently leading to strong distrust of travel demand prediction (Hyodo 2002). The other extreme method is to regard quantitative demand prediction and policy evaluation as an unnecessary procedure in the planning process, because uncertainties cannot be fully eliminated. Although the latter treatment has not been practiced, especially not in large-scale projects, this type of decision mindset certainly exists. However, this view may also be problematic, because arbitrariness in policy decisions cannot be avoided. A single collective decision on planning must be reached even when people have a wide range of opinions. For this purpose, maximum objectivity of judgments should be ensured, and quantitative analysis is expected to play a significant role in this process.

Although the above two methods are attractive because they avoid arguments over uncertainties that make policy decisions difficult, the optimal method may lie between the two extremes. We should neither rely completely on the prediction and quantitative policy evaluation nor ignore the importance of quantitative analysis. It is important to understand the uncertainties in the transportation planning process as much as possible and to make appropriate use of quantitative analysis (especially travel demand prediction). In this sense, although the question of what remains unknown is an open-ended one, more attention should be paid to answering it.

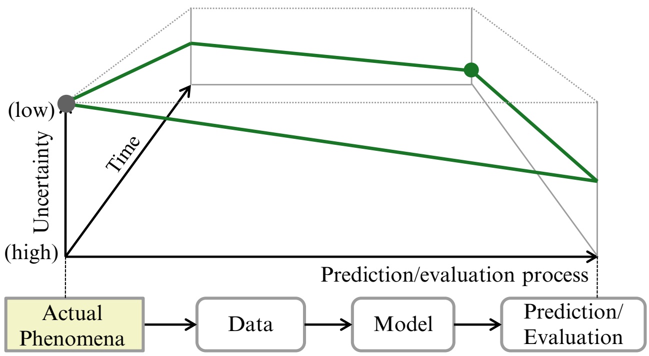

Fig. 11.1 Uncertainties in future prediction and the subsequent policy evaluation

11.1.2 The Focus of This Chapter

In this chapter, we limit our focus to uncertainty regarding travel behavior, which is one of the main sources of uncertainty in travel demand prediction and subsequent policy evaluation. In general, travel demand predictions and policy evaluations are made by eliciting and consolidating information regarding variations in, and changes to, travel behavior, and then using this information to infer the future state and policy impacts, given certain assumptions and conditions. More specifically, data are usually collected from the actual phenomena and used to develop a model to predict future demand and to evaluate policy. Researchers often focus on several indicators, such as value of travel time and price elasticities of travel demand, to transform complex data from actual transport phenomena into manageable and intuitively understandable information. Moreover, they make predictions and evaluations, usually under the assumption that behavioral mechanisms do not change over time.

Uncertainties in the above typical prediction/evaluation process can be graphically represented as shown in Fig. 11.1, where two types of uncertainties are illustrated: those in the prediction/evaluation process and those in the projection of future states. The difference between these two types of uncertainty is that, in essence, the former is procedural uncertainty while the latter arises from actual phenomena.

The remainder of this chapter is organized according to the above perspectives. After defining the terms used in this study, Sect. 11.2 discusses the observation of travel behavior on which the analysis is based. Section 11.3 focuses on the uncertainties that arise during the prediction/evaluation process by examining variations in travel behavior. We then investigate changes in travel behavior, exploring the uncertainties arising from projections of future states. In Sect. 11.5, we discuss the implications for transportation planning of knowing uncertainties.

11.1.3 Terminology

The term "uncertainty" has different meanings depending on context, and researchers have used it in different ways. Knight (1921) distinguished uncertainty from risk: uncertainty indicates that both outcome and the occurrence probability are unknown, while risk indicates that the outcome is unknown but the occurrence probability is known. On the other hand, in practice, a number of researchers use the term "uncertainty" to express what Knight calls risk. For example, a probabilistic treatment of input data is sometimes called uncertainty (Morgan and Henrion 1990). On the other hand, some researchers use the term "risk" even when the probability is unknown (Flyvbjerg et al. 2003). Actually, while it is not difficult to distinguish between uncertainty and risk in theory, it is often difficult in practice. This is because in some cases, "uncertainty" can be converted into "risk" by accumulating knowledge, and thus there are ambiguous relationships between uncertainty and risk in a practical sense. Therefore, this study uses the term "uncertainty" to represent both the uncertainty defined by Knight and risk.

As mentioned above, this study explores uncertainties in two areas: variations and changes in travel behavior. *Variations* are defined here as fluctuations in, or dispersions of, behavior observed over a given period that is sufficiently short to assume stability in the causal structure of behavior (i.e., relations between the target behavior and its determinants). Variations may arise from various sources, including interindividual variations (such as differences in age or gender) and intraindividual variations (such as differences in time pressure or travel party). Some of these can be observed from explanatory information, while the rest cannot. *Changes* are defined as structural changes in behavioral mechanisms over time (i.e., a causal structure of behavior creates different states over time). Here an intrinsic practical difficulty in clearly distinguishing between variations and changes similar to the ecological fallacy should be noted (Robinson 1950). How close together in time must two observations be in order to regard differences between them as variations rather than actual changes in behavior? Can temporal averages in behavior be regarded as typical? This temporal version of the ecological fallacy arises when attempting to distinguish between variation and change empirically. In the following analyses, differences between observations are basically regarded as a source of variation when the observations are made within a year. Otherwise, we regard the difference as a source of changes. These distinctions may be intuitively reasonable, but exploring this temporal version of the ecological fallacy remains as an important future task.

11.2 Observations of Travel Behavior

The observation of travel behavior plays a fundamental role in travel behavior analysis, because the qualities of the subsequent steps (such as modeling of travel behavior and policy evaluation) are conditional on data quality. In general, the fewer the data that are available, the stronger the assumptions needed to infer a future state.

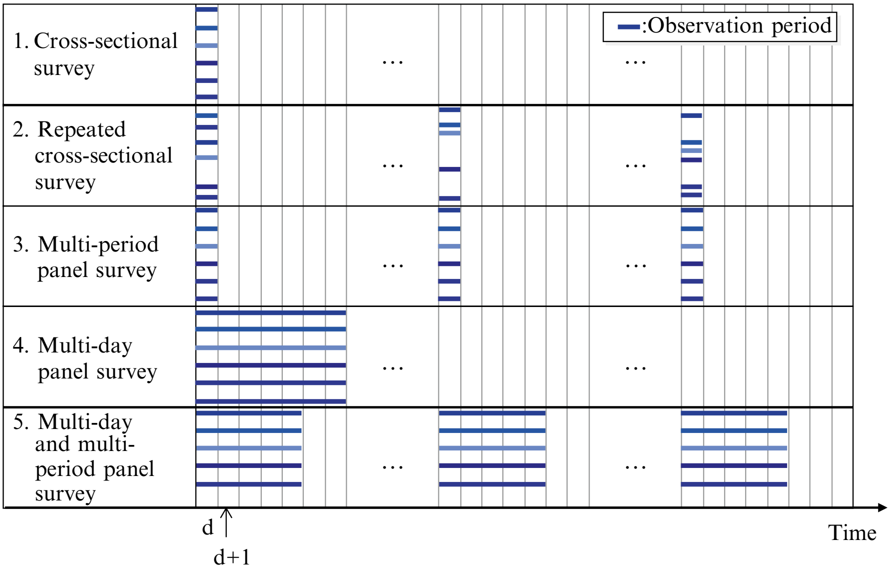

Fig. 11.2 Surveys for observing behavioral variations and changes

Thus, obtaining richer data at lower cost is an important aspect of behavioral observations in practice. In this section, we first introduce types of survey methods for observing changes and variations in travel behavior, and then we discuss sampling designs under budget constraints.

11.2.1 Behavioral Observation: Types of Surveys

Figure 11.2 shows five types of surveys differentiated by richness of information on changes and variations in travel behavior. A traditional survey of travel behavior is cross-sectional. In a typical cross-sectional survey (such as a traditional person–trip or travel diary survey), respondents are asked to report their travel behavior on a given day. Future travel demand can be predicted by assuming that (1) the travel behavior observed on the survey day is typical of all other days, that is, that travel behavior is highly repetitious in the short run, and (2) the behavior elicited from the data does not change over time. However, we can easily imagine situations in which actual behavior does not support these two assumptions. For example, travel behavior certainly varies between weekdays and weekends because activity needs are different. It can also be expected that sensitivity to travel cost may decrease with economic development. Efforts have been made to overcome these limitations. One simple method is to apply repeated cross-sectional surveys, which can partially support the validity of the above assumptions, such as changes in behavior that occur with changes in socioeconomic circumstances. On the other hand, although repeated cross-sectional data may be suitable for measuring behavioral changes at the macroscopic level, they cannot provide information on behavioral changes at the microscopic level, such as the impacts of life-shock events (Clarke et al. 1982). In addition, Hanson and Huff (1988) pointed out the following.

> Say, 10% of a sample group rode the bus on the survey day. One interpretation is that 10% of the population always rides the bus (thereby attributing all of the observed variance to inter-personal variability); at the other extreme is the interpretation that everyone in the population rides the bus 10% of the time (thereby attributing all the variance to intrapersonal variability). Clearly a mixture of these two sources of variability gives rise to the observed outcome, but we cannot ascertain the relative importance of each with cross-sectional data.

Importantly, this indicates that some policy questions, such as the equity of accessibility to bus services, cannot be properly answered with cross-sectional and repeated cross-sectional data. To overcome such limitations, longitudinal information is needed (Hanson and Huff 1988). On the other hand, it has also been pointed out that in some cases, repeated cross-sectional data can be superior to panel data (Yee and Niemeier 1996). For example, for long-term behavioral changes (e.g., changes over 20 years), panel data cannot represent the overall patterns of a population's activity/travel because data from younger generations are usually not included. Additionally, long-term observation of the same individuals is quite difficult for various reasons—for example, because of changes in residence. Repeated cross-sectional data may be suitable for measuring long-term behavioral changes, although they cannot provide information on behavioral changes at the microscopic level. In brief, repeated cross-sectional data have both advantages and disadvantages compared with panel data, and they may be a useful source of information on macroscopic changes.

Regarding longitudinal surveys, there are three types of survey: multiperiod panel surveys, multiday panel surveys, and multiday and multiperiod panel surveys. In all of these, variables are measured in the same units over time. Multiperiod panel survey data are collected to observe travel behavior repeatedly at discrete points of time. The basic purpose of this type of survey is to capture changes in activity/travel behavior. Unlike repeated cross-sectional surveys, the data contain information on changes at the microscopic level. On the other hand, it is usually difficult to identify whether the difference between behaviors observed at two points in time actually comes from changes in behavior; that is, the problem of separating changes and variations may emerge. For example, the difference in departure time choices between two points in time may be caused not only by changes in a person's job but also simply by variations in daily behavior because of physical conditions. In the latter situation, the observed differences should be understood as variations, not as changes.

The second type of longitudinal survey, a multiday panel survey, is used to observe travel behavior on multiple consecutive days. From this type of data, the source of variations can be distinguished. Specifically, intra- and interindividual variations can be distinguished, allowing us to respond to Hanson and Huff's (1988) criticism mentioned above. Moreover, this type of data has contributed greatly to the sophistication of travel behavior models such as that in the activity-based approach (e.g., Kitamura 1988). Commonly cited case studies of multiday panel surveys are the Uppsala Household Travel Survey (Hanson and Huff 1988), the Reading

Activity Diary Survey (Pas 1986), Mobidrive (Axhausen et al. 2002), the REACT! Survey (McNally and Lee 2002), the Twelve Week Leisure Travel Survey (Stauffacher et al. 2005), and the Swiss Longitudinal Travel Survey (Axhausen et al. 2007). In Japan, this type of survey has also been widely implemented in the form of the probe-person survey.[1]

Although both multiperiod and multiday panel surveys are important sources of information on changes and variations in travel behavior, they cannot simultaneously capture both. Simultaneous observation is especially important for capturing changes in travel behavior at the microscopic level while avoiding the problem of separating changes and variations mentioned above. For this purpose, a multiday and multiperiod panel survey may be needed. Commonly cited examples are the Dutch Mobility Panel (Van Wissen and Meurs 1989), the Puget Sound Travel Panel (Goulias et al. 2003), the Toronto and Quebec Travel Activity Panel Survey (Roorda et al. 2005), and the German Mobility Panel.[2] Importantly, researchers cannot know how much they do not know about travel behavior changes at the microscopic level without rich data. Therefore, although implementing a multiday and multiperiod panel survey is costly, it is useful for confirming or rejecting the assumptions made in the conventional and practical analysis. The cost effectiveness of sampling designs will be discussed briefly in the next subsection.

11.2.2 Sampling Designs

Although multiday and multiperiod panel data are useful, as discussed in the previous subsection, they are costly and require good institutional organization (e.g., Zumkeller 2009). Thus, multiday and multiperiod panel surveys are seldom implemented in practice. On the other hand, there are several pieces of evidence for the importance of collecting panel data, even from the viewpoint of cost effectiveness. For example, Pas (1986) examined the optimal length (in days) for multiday panel surveys and underscored the substantial benefits of multiday panel surveys in reducing data collection costs and/or improving the precision of parameter estimates. Kitamura et al. (2003) focused on the design of multiperiod panel surveys in the context of discrete travel behavior and concluded that continuous behavioral observations are needed to detect changes in behavior. This implies that to identify changes in behavior, short-term variability must be explicitly distinguished from long-term changes (i.e., the separability problem of variations and changes must be dealt with), indicating that multiday and multiperiod panel survey data are required. In line with this view, Chikaraishi et al. (2013) explored the optimal survey designs for multiday and multipanel surveys.

Figure 11.3 shows the basic concept of survey designs for multiday and multiperiod panel surveys. In this type of survey design, there are three aspects of

[1] http://www.probe-data.jp/eng/index.html (accessed on November 2, 2012).

[2] http://mobilitaetspanel.ifv.uni-karlsruhe.de/en/index.html (accessed on November 2, 2012).

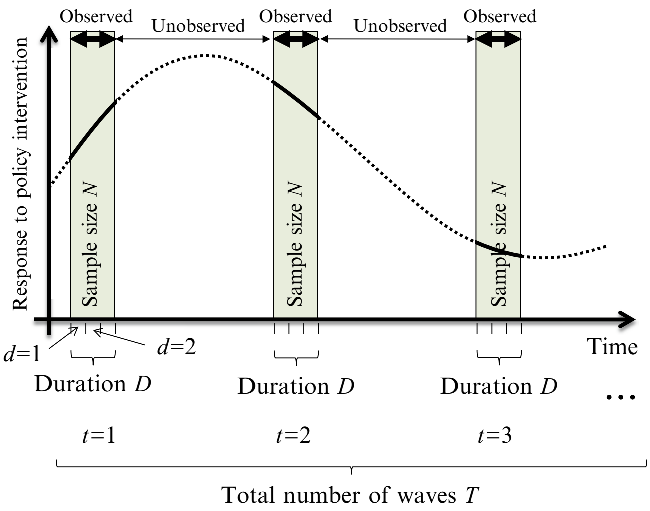

Fig. 11.3 Survey designs for multiday and multiperiod panel survey (Chikaraishi et al. 2013)

behavioral observation: (1) the observed duration of each wave, denoted by D [day/wave], (2) the total number of waves conducted in a certain survey period, denoted by T [wave], and (3) the sample size, denoted by N [people]. Practical examples include the fourth person–trip survey in the Tokyo metropolitan area, in which $\{N, T, D\} = \{883044, 1, 1\}$, the Mobidrive survey (Axhausen et al. 2002), with {361, 1, 42}, and the German Mobility Panel (Zumkeller 2009) with {1800, 17, 7}. Thus, survey designs vary. Moreover, because of budget constraints, the trade-off between the observed duration of each wave, the interval between successive waves, and the sample size in the survey designs must be considered, depending on the purpose of the survey. On this subject, Chikaraishi et al. (2013) showed that with an increase in the complexity of behavioral changes, not only shorter intervals between waves but also longer multiday behavioral observations per wave are necessary.

11.3 Variations in Travel Behavior

11.3.1 The Importance of Exploring Behavioral Variations

Variations of travel behavior reveal information on uncertainties in terms of imperfect fit of models to data. Decisions related to travel behavior are influenced by different factors at various levels, such as sociodemographic, locational, and other contextual attributes. Considering that an individual decides his or her behavior according to the constraints of time and space as well as his or her own current situation (Hägerstrand 1970), the dominant types of variation could be intraindividual, interindividual, interhousehold, temporal (i.e., systematic day-to-day variation), or spatial.

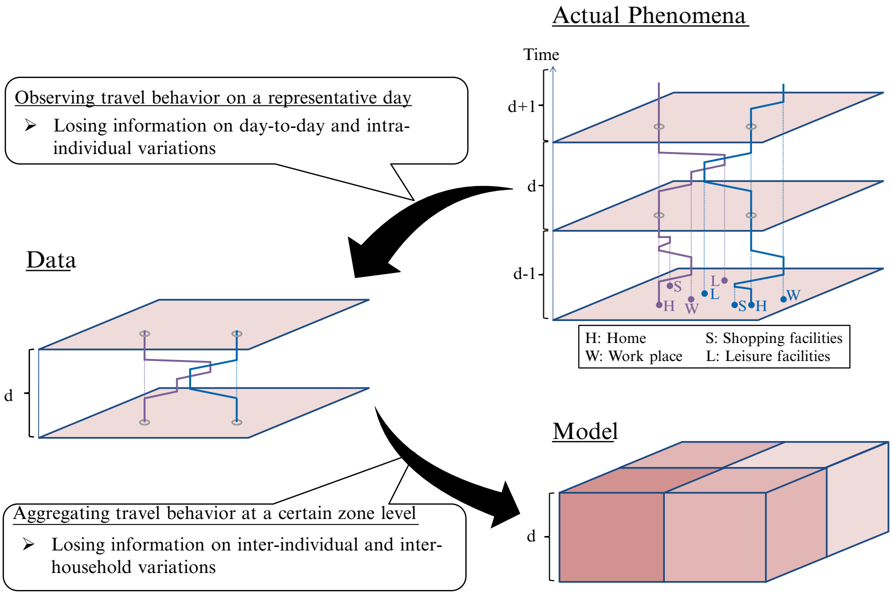

Fig. 11.4 A traditional travel demand prediction process

In fact, the existence of such types of variations is recognized by researchers, and the importance of discriminating among them has been discussed extensively (e.g., Pas 1987; Hanson and Huff 1988; Pas and Sundar 1995; Kitamura et al. 2006; Schlich and Axhausen 2003).

In general, explaining these behavioral variations based on observed elements is what an empirical model usually does. In addition, mainly because of data limitations, some sources of unobserved variation remain even after explanatory information is introduced. For example, if household income is not available but has some effect on behavior, the unobserved interhousehold variation would be greater than that with income effects considered. A lack of situational attributes (e.g., "with whom" and "for whom") may lead to greater unobserved intraindividual variation than with those attributes considered. Moreover, when a travel demand model, such as a traditional four-step model, is developed based on spatial aggregation data, information on day-to-day variations and intraindividual variations is lost at the data collection step, as is information on interindividual and intraindividual variations at the model development step (Fig. 11.4).

In this study, we attempt to identify sources of variations in various aspects of behavior and assess the possibility of explaining these variations with further information. There are at least three reasons why understanding the properties of variation is important.

First, before attributing behavioral variations to observed elements, it is necessary to understand what kinds of variations exist by exploring the fundamental properties of the behavior. In reality, analysts must narrow the target of analysis to limited variation types in many cases. This is mainly because of the available data, analysis methods, or both. For example, it is intrinsically impossible to capture temporal variations using survey data from a single day (Pas 1987), but multiday surveys are costly and often impossible to conduct in practice. In other instances, interindividual variation is automatically lost in traditional four-step models using spatial aggregate data, but such models are still often employed, partly because alternative methods are obscure. Because such limitations cannot be avoided in certain situations, especially in current practice, the focus on limited variation types should be understood. In other words, it is necessary to quantify the loss of information caused by ignoring some kinds of variations.

Second, it may be useful to clarify what kinds of variations are difficult to capture even after observed elements are introduced into models. The remaining unobserved variations may indicate niches to be exploited further, probably along with additional observations. In line with this, Kitamura (2003) pointed out that even if one could grasp an actual "stable" relationship between phenomena, it would be impossible to understand the phenomena themselves without analyzing how they vary around the stable relationship. The remaining variations could offer useful information to reveal variation in the behavior around the stable relationship and to suggest what kinds of factors should be further observed.

Third, related to the first and second points, information on variation properties could contribute to a better understanding of potential fallacies in the analysis. For example, a number of researchers have confirmed the risk of the aggregative (ecological) fallacy (Robinson 1950) in relation to aggregate models (i.e., four-step models) and the representative fallacy in relation to disaggregate models. The representative fallacy can be seen as an issue arising from the assumption that individual behavior varies little from day to day and that the behavior on a typical day can be used to represent almost all behavior on other days. These fallacies indicate that more detailed and microscopic behavioral analysis is needed. On the other hand, microscopic level analysis can also be strongly affected by the "atomistic fallacy" (Diez-Roux 1998), which is the fallacy of modeling behavior exclusively on a given microscopic level unit while ignoring macroscopic level effects. In the transportation literature, the aggregative fallacy has received much more attention than its counterpart, the atomistic fallacy. In the real world, the unit of analysis can be defined at various levels. For example, the macroscopic level could be defined according to a city or a zone, and the microscopic level according to a household, an individual, an activity episode, or a trip. Basically, the more microscopic level units are employed as basic units of analysis, the more likely the research into the effects of macroscopic level variables on behavior should be discouraged, and vice versa. Information on various types of observed and unobserved variation could remind us of these potential fallacies.

11.3.2 Empirical Findings on Behavioral Variations

As mentioned above, there are five main variation types: intraindividual, interindividual, interhousehold, day-to-day (temporal), and spatial variations. In this subsection, we introduce empirical findings regarding the properties of the five variation types proposed by Chikaraishi et al. (2009, 2010a, 2011a). They explore the properties of these variations using a multilevel modeling approach (Hox 1995; Kreft and de Leeuw 1998; Goldstein 2003):

$$F\left(y_{tihds}\right) = \beta \mathrm{x}_{\mathrm{tihds}} + \gamma_{ih} + \gamma_{h} + \gamma_{d} + \gamma_{s} + \varepsilon_{tihds} \tag{11.1}$$

where F() is the response function in generalized linear models, y_{tihds} is the dependent variable of the tth trip made by person i of household h on day d in space s, β is a vector of unknown parameters, $\mathrm{x}_{\mathrm{tihds}}$ is a vector of explanatory variables, and γ_{ih}, γ_h, γ_d, γ_s, and $\varepsilon\gamma_{tihds}$ are random components that indicate unobserved interindividual, interhousehold, temporal (day-to-day), spatial, and intraindividual variations, respectively. It is also assumed that all random components are normally distributed with a mean of zero and variance $\sigma_{ih}^2, \sigma_h^2, \sigma_d^2, \sigma_s^2$ and σ_0^2, respectively. Equation (11.1) is used when the unit of analysis is "trip" (e.g., departure time and travel mode choice), while suffix t may be omitted from Eq. (11.1) when the unit of analysis is "person-day" (e.g., activity generation and time use for a single day).

In the model without explanatory variables (called the *Null* model), the total variation of $F(E[y_{tihds}])$ can be calculated as:

$$\mathrm{Var}\left(F\left(y_{tihds}\right)\right) = \tilde{\sigma}_{ih}^2 + \tilde{\sigma}_h^2 + \tilde{\sigma}_d^2 + \tilde{\sigma}_s^2 + \tilde{\sigma}_0^2 \tag{11.2}$$

where "~" indicates the estimated parameters of the *Null* model. Based on the variation properties in the *Null* model, it is possible to clarify which source of variation affects behavior.

When the model includes explanatory variables (called the *Full* model), the total variation of $F(E[y_{tihds}])$ can be calculated as:

$$\mathrm{Var}\left(F\left(y_{tihds}\right)\right) = \mathrm{Var}\left(\hat{\beta}\mathrm{x}_{\mathrm{tihds}}\right) + \hat{\sigma}_{ih}^2 + \hat{\sigma}_h^2 + \hat{\sigma}_d^2 + \hat{\sigma}_s^2 + \hat{\sigma}_0^2 \tag{11.3}$$

where "^" indicates the estimated parameters of the *Full* model.

Theoretically, all estimated variation components of the random components in the *Full* model should be smaller than those in the *Null* model because $\mathrm{Var}(\hat{\beta}\mathrm{x}_{\mathrm{tihds}})$ explains part of the total variation. It is further expected that increasing the number of explanatory variables decreases the variances $\sigma_{ih}^2, \sigma_h^2, \sigma_d^2, \sigma_s^2$ and σ_0^2. As mentioned above, it is interesting to know how much of these variances are explained for several reasons. The main reason is that remaining variation offers information about which types of explanatory variables are still lacking and which direction future research should take. For example, if the specified set of explanatory variables does not reduce spatial variation or if it remains high, more attention should be paid to observing spatial variables. However, determining which explanatory variables reduce the unobserved heterogeneities is less certain because microscopic level variables in particular have cross-level influences, and it is rare to eliminate unobserved variation at one level completely (Teune 1979). For example, the duration of a commute may be categorized as a situational attribute, but it is not difficult to imagine that there are substantial differences between individuals or O–D pairs.

Therefore, a model including duration of commute as an explanatory variable may reduce not only intraindividual variation but also other variation. Thus, in the following discussion of empirical findings, we mainly focus on the variation properties of various behavioral aspects, rather than on which factor is the ultimate source of behavioral variations.

The variation decomposition technique based on the multilevel modeling approach can be applied to a number of behavioral aspects, as long as the behavioral model can be regarded as a generalized linear model such as a linear regression model, binary choice model, multinomial choice model, or some types of discrete-continuous model. In the following discussion on empirical findings, we consider four behavioral aspects: departure time, activity participation, time use, and mode choice.

11.3.2.1 Behavioral Variations Without Explanatory Information

Figure 11.5 shows the variation properties of departure time, activity participation, time use, and mode choice (Chikaraishi et al. 2009, 2010a, 2011a; Chikaraishi 2010). All variation properties were estimated using Mobidrive data, which are continuous 6-week travel survey data collected in the cities of Karlsruhe and Halle, Germany, in 1999 (Axhausen et al. 2002). These data represent one of the longest multiday travel diary panel surveys, and they may be suitable for exploring the variation properties of behavioral aspects.

The major findings from Fig. 11.5 can be summarized as follows:

1. Larger interindividual variations are observed for mandatory activities (school and work) in departure time, activity participation and time use. Thus, it can be expected that variations of mandatory activities mainly arise from differences across individuals. On the other hand, it can also be confirmed that interindividual variations are smaller in recreational activities (nondaily shopping and leisure) for departure time, activity participation, and time use.
2. The proportion of intraindividual variation is substantial in most cases, except for variation properties of mandatory activity participation and time use, and all travel modes. This implies that it may be inappropriate to assume that individual behavior changes little from day to day and behavior on a typical day remains constant. In other words, multiday panel data may be needed to explore the mechanisms of behavioral aspects.
3. On the other hand, the variation properties of mode choices show smaller day-to-day and intraindividual variations, meaning that mode choice behavior is relatively stable from day to day compared with other behavioral aspects.
4. It is confirmed that a substantial amount of variation information may be lost when we use spatial aggregated data in a traditional four-step model.

Although the empirical findings shown here are conditional on the models employed, it may be useful to revisit the validity of the current demand prediction procedure, shown in Fig. 11.4. In other words, knowing about such variation properties informs us about the limitations of the current prediction procedure, which focuses on a limited number of variation types.

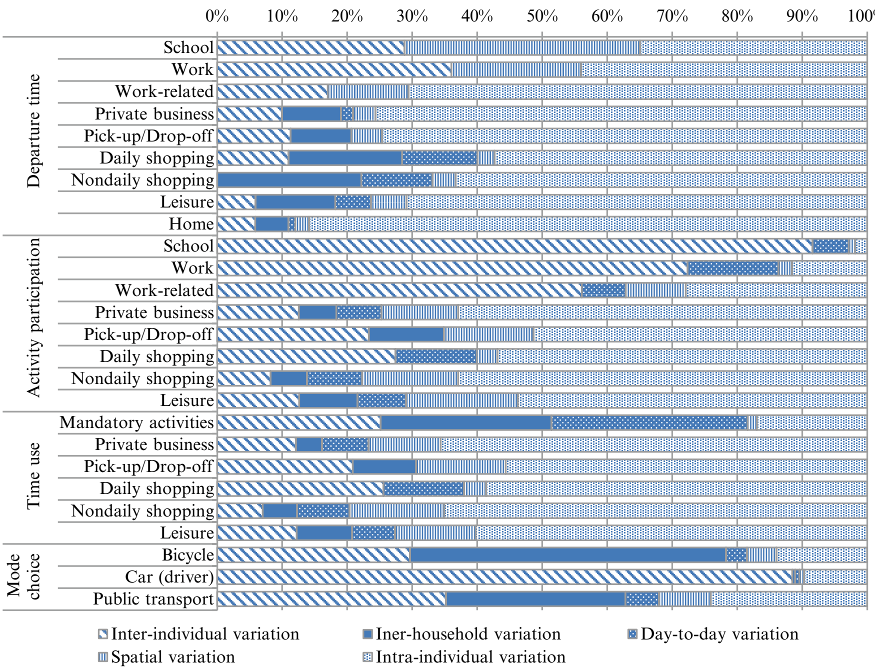

Fig. 11.5 Estimated behavioral variations (without explanatory information). *Notes*: (1) The estimation results of departure time model from Chikaraishi et al. (2009). A multilevel linear regression model was applied to obtain the variation properties. (2) The estimation results of activity participation model from Chikaraishi (2010). A multilevel binary logit model was applied. (3) The estimation results of time use model from Chikaraishi et al. (2010a). A multilevel MDCEV (Multiple Discrete-Continuous Extreme Value) model was applied. (4) The estimation results of mode choice model from Chikaraishi et al. (2011a). A multilevel multinomial logit model was applied. (5) The definitions of spatial variations vary across case studies. See the above cited papers for the details. (6) Since the utility in the MDCEV model and logit model has no absolute reference or zero point, one has to consider the relative value of utility to obtain variation properties. In-home activities (Car Passenger) were treated as a reference alternative for obtaining the variation properties of other alternatives in time use (mode choice) behavior

11.3.2.2 Behavioral Variations with Explanatory Information

Next, we examine how much of the unobserved variances of random components can be explained by observed information. Here we only focus on the results of departure time choice (Chikaraishi et al. 2009). The results of time use and mode choice are also available from Chikaraishi (2010) and Chikaraishi et al. (2011), respectively. The additional data needed to capture variations in departure time include:

- [Individual attributes] gender, marriage status, employment status, age, and vehicle license;
- [Household attributes] number of household members, number of children in household, number of personal vehicles, distance to the nearest bus stop/LRT/rail station, and household income; [spatial attributes] residential locations;

- [Temporal attributes] day-of-week; and
- [Episode unit attributes] travel time, number of activities per day, size of party, and travel mode.

Explanatory variables were selected based on a preliminary analysis conducted to select statistically significant variables (at least at the 90 % level of significance). The selected variables vary from activity to activity (the details can be found in Chikaraishi et al. 2009). The additional data provide a fair representation of the variables used in practical models.

Figure 11.6 shows the estimated variation properties of departure time. First, it is found that most temporal variation can be explained by the additional data introduced above. More specifically, more than 70 % of temporal variation in private business, daily shopping, nondaily shopping, leisure and home is captured. The reason may be twofold. First, the introduced day-of-week dummy works well to reduce such variations. Second, introducing other types of variables may also reduce such temporal variation. For example, some activities in which two or more household members participate could occur more frequently on holidays. In such cases, introducing the relevant information could reduce temporal variation.

The smallest reduction of unobserved variation is observed in intraindividual variation (4–16 %). Explaining intraindividual variation using variables appears quite difficult for all activity types. This implies that, at least in departure time choice, additional information is needed to capture intraindividual variations. As for other components of variations (interindividual, interhousehold, and spatial variation), the reduction of unobserved variation varies greatly with activity type; interindividual variation ranges from 20 % to 83 %, interhousehold variation from 27 % to 65 %, and spatial variation from 30 % to 82 %. However, for almost all activity types, significant amounts of unobserved interindividual, interhousehold and spatial variation remain, suggesting that it is necessary to introduce further appropriate observed variables to explain it. In this way, this type of analysis can provide a fundamental picture of what we do not know about the mechanisms of travel behavior.

11.4 Changes in Travel Behavior

11.4.1 Types of Behavioral Changes and Data

Changes in travel behavior contain information on uncertainty about the similarity of the future to the past. Behavioral changes can occur at both microscopic and macroscopic levels (Pendyala and Pas 2000). The former changes could occur along with changes in areas such as jobs, life cycle stages, or home location. Lifestyle change is another important factor causing microscopic level changes. Macroscopic level changes can occur along with changes in socioeconomic circumstances, such as the development of information technology, an aging population, and a diminishing

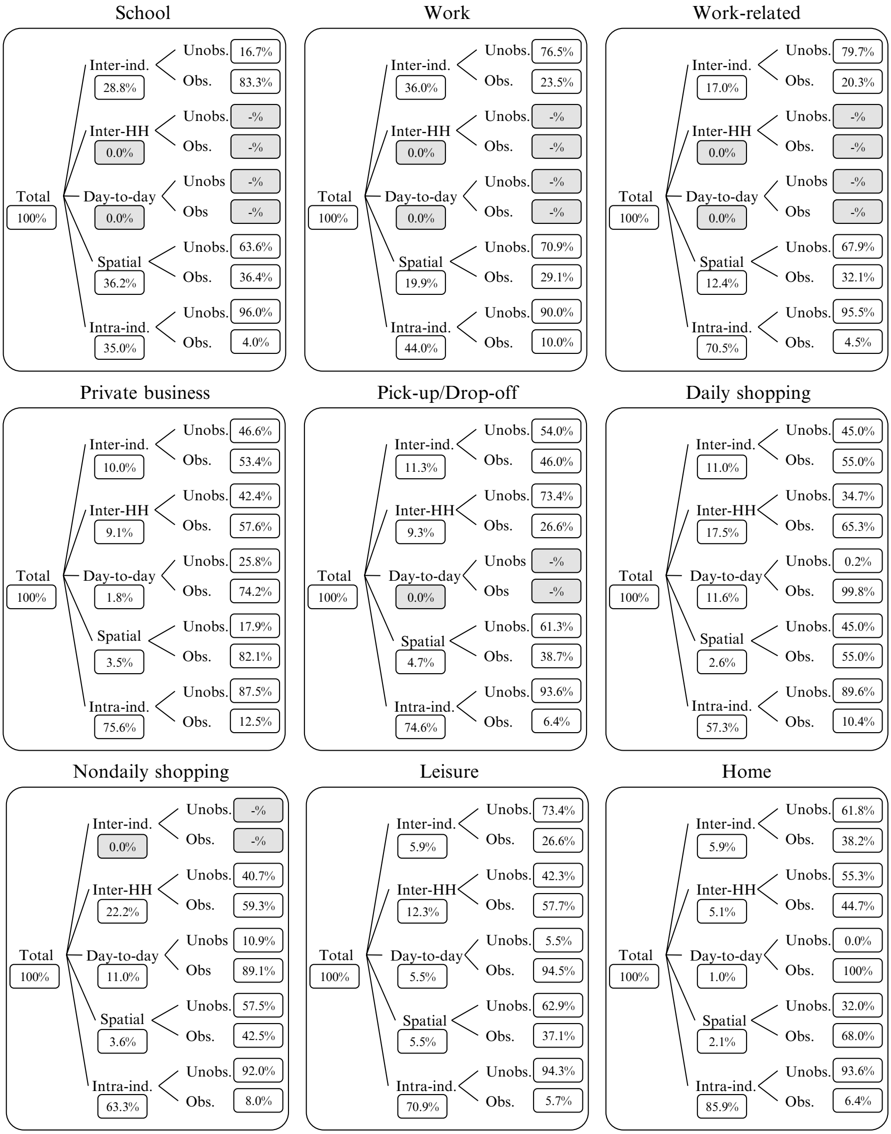

Fig. 11.6 Estimated behavioral variations in departure time (with explanatory information) (Chikaraishi et al. 2009)

number of children. Although it may be expected that the cumulative effects of microscopic changes will cause macroscopic changes, it can also be expected that macroscopic level changes will eventually cause a gradual shift in the degree of changes at the microscopic level. For example, the diminishing number of children may be expected to keep elderly people working longer, and as a result, the impact and timing of a “life-shock event” could be changed. In addition, changes in technologies can cause changes in individual travel behavior; for example, through telecommuting. Thus, it can naturally be considered that microscopic and macroscopic states typically coevolve (Epstein 2006).

To capture behavioral changes at the microscopic level, panel data are required. For example, developing dynamic behavioral models (Hensher 1988; Kitamura 1990) and exploring individual transitional behavior (Goulias 1999; Thøgersen 2006) are impossible without panel data. On the other hand, to investigate macroscopic level changes in addition to panel data, repeated cross-sectional data in which an independent sample is collected at each time point could be used. For example, aggregated observations of changes and monitoring trends in behavior (Levinson and Kumar 1995) and the temporal (in)stability of a population’s (or macro) activity–travel patterns (Zahavi and Talvitie 1980) could be confirmed using repeated cross-sectional data. Moreover, aggregated time-series data usually contain much longer continuous period information, although these are mostly aggregated data where most variation information is lost because of the aggregation procedure discussed above.

Considering the advantages and disadvantages of different types of data, this section introduces three empirical studies. First, we show changes in traffic demand elasticities (for details refer to Chikaraishi et al. 2010b). This study was conducted using traffic volume data, which are easily accessed time-series data. Second, behavioral variations in time use are introduced (Chikaraishi et al. 2012). This study uses repeated cross-sectional time-use data. Third, we briefly introduce the empirical findings regarding variations in travel time expenditure (Chikaraishi et al. 2011b). In the third case study, multiday and multiperiod data were applied, allowing us to distinguish between interindividual and intraindividual variations.

11.4.2 Changes in the Response to Certain Variables: Traffic Demand Elasticities

First, we examine the spatiotemporal changes of traffic demand elasticities regarding gasoline prices, focusing on the substantial fluctuations that occurred throughout 2008 in Japan. The analysis uses monthly traffic volume data collected on 53 expressways, which are automatically collected by the traffic counter devices installed on roadsides. The elasticities are calculated based on a log-transformed Cobb–Douglas demand function that has been widely used in practice. We directly extend this traditional model to capture the spatial and temporal instability of the elasticities by first building a random coefficient model to represent spatial heterogeneity and then applying a sequential Bayesian updating method to examine monthly changes in these elasticities.

Figure 11.7 shows the spatiotemporal changes in traffic demand elasticities. The results indicate that although most monthly changes in the average elasticities over

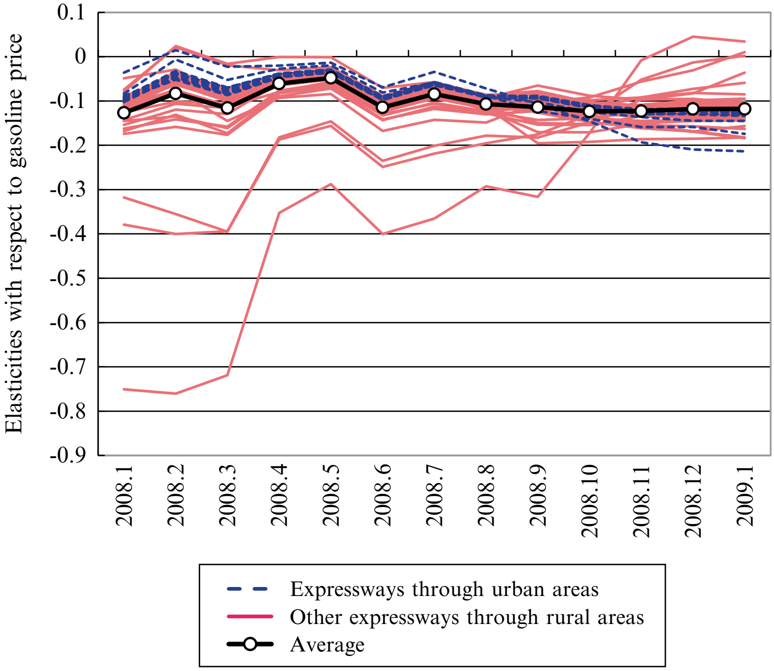

Fig. 11.7 Changes in traffic demand elasticities (Chikaraishi et al. 2010b)

all routes were observed before August 2008, different directions of change across routes were observed after September 2008, when gasoline prices began to fall. The results also indicated that responses to gasoline price changes depend on the causes of price changes. Furthermore, on urban expressways, it was found that once a reduction in traffic demand was attained because of rising gasoline prices, demand did not fully recover even after the actual prices fell again to the original level.

Although this analysis focused on unusually strong fluctuations in gasoline prices, such events often occur. This indicates that even when a plausible parameter value for future demand prediction is obtained, continuous monitoring of parameter changes may be needed, especially when the policy can be adjusted over time. On the other hand, information on behavioral changes based on such aggregated data is still limited because the intraindividual, interindividual, and interhousehold variations have not been taken into account in the aggregated analysis.

11.4.3 Changes in Behavioral Variations: Time-Use Behavior

Compared with aggregated time-series data, repeated cross-sectional data contain more detailed information on travel behavior. This subsection introduces the

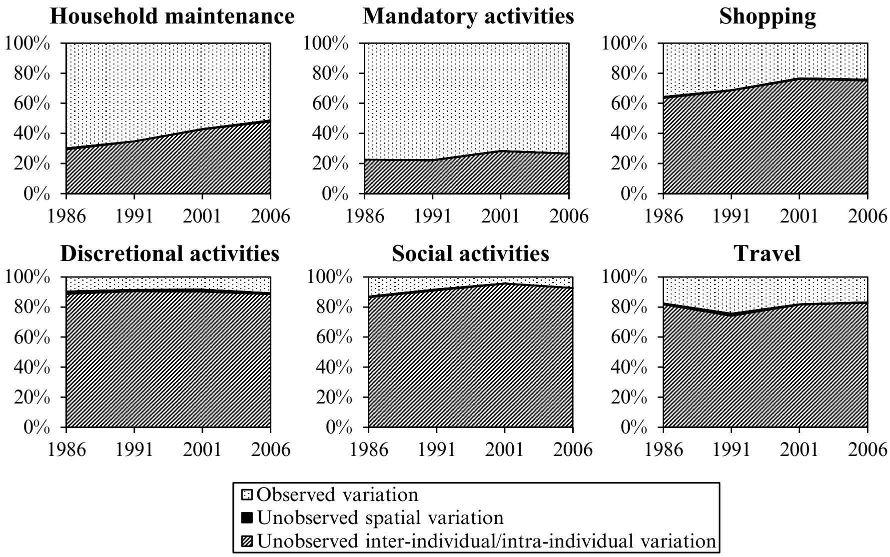

Fig. 11.8 Changes in variations in time use behavior (Chikaraishi et al. 2012)

estimation results of the long-term changes in cross-sectional variations in time-use behavior by Japanese people using a multilevel MDCEV model as in Chikaraishi et al. (2012). The basic methodology is the same as that in the previous section, but the definition of variations is different. Specifically, cross-sectional variations include interindividual/intraindividual variation and spatial variation (at the prefecture level). Here it should be noted that interindividual and intraindividual variation cannot be separated because repeated cross-sectional data cannot distinguish between them. Despite this, this analysis may provide useful information on changes; for example, whether structural changes in time-use behavior have led to diversification (again, we cannot distinguish whether the diversification occurs between or within individuals). The empirical analysis was conducted using national time-use data collected at four points in time (1986, 1991, 1996, and 2001) from the "Survey on Time Use and Leisure Activities" conducted by the Japanese Ministry of Internal Affairs and Communications.

Figure 11.8 shows the changes in variation properties of time-use behavior. The most important finding here is that given the explanatory variables used in the empirical analysis (i.e., work style, car ownership, income, age, and gender), increased effects of unobserved interindividual variations in household maintenance and shopping are evident in Japanese time-use behavior. This implies that patterns in behavior become more evident over time, and it may be difficult to predict activity–travel patterns in the long term. In other words, structural changes in time-use behavior have resulted in diversification.

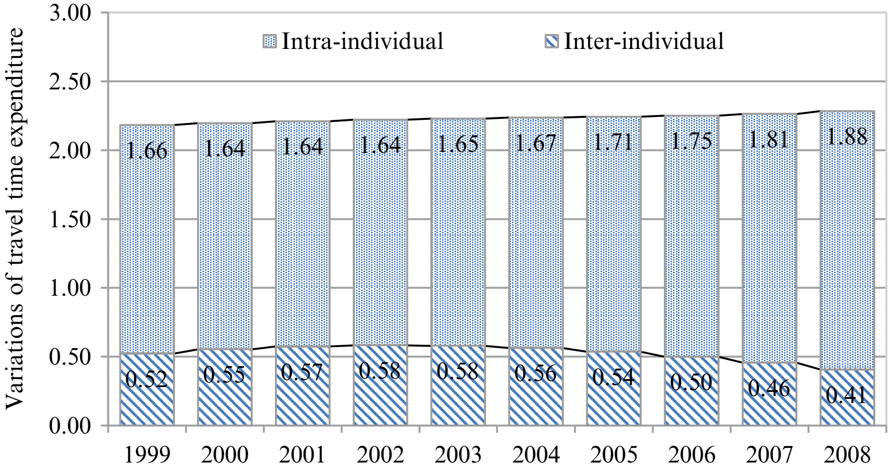

Fig. 11.9 Changes in variations in travel time expenditure (Chikaraishi et al. 2011b)

11.4.4 Changes in Behavioral Variations: Travel Time Expenditure

Although a tendency toward behavioral diversification was shown above, we did not clarify the source; that is, diversification within an individual or diversification between individuals. In this section, we conduct an empirical analysis of changes in travel time expenditure, distinguishing between intraindividual and interindividual variations, following Chikaraishi et al. (2011b). The methodology is a simple extension of the multilevel models introduced in the previous section: all parameters are assumed to be functions of time, including variance parameters; thus, the estimated variation properties can change over time. In the empirical analysis, a multilevel Tobit model was applied to take into account zero travel time expenditure; that is, days when a person is immobile. The analysis considers interindividual and intraindividual variations. Although theoretically we can incorporate other types of variations, such as spatial and temporal, the variation types were restricted to reduce the cost of estimation. The data used in the empirical analysis are from the German Mobility Panel, which is a multiday and multiperiod panel survey.

The empirical results are shown in Fig. 11.9. The empirical results indicate that intraindividual variations increase over time, whereas interindividual variations become smaller. This suggests that over time, people's travel time expenditures become more dependent on situational attributes than on individual or household attributes. The implication is that travel time expenditure diversifies for an individual; that is, observed travel time expenditure may become sensitive to the immediate situation. This finding means that description of travel behavior based on conventional data for 1 day may become less accurate over time. A longer observation period for each wave may be more important for capturing behavioral changes.

11.4.5 Summary of Behavioral Changes

We have briefly introduced the results of three empirical analyses, focusing on changes in travel behavior. The first empirical study indicates that the transport-related indicator is not truly stable over time. The second empirical study indicates that modeling travel behavior becomes difficult over time given a specific set of explanatory information, implying that more detailed behavioral observation and/or more sophisticated modeling techniques may be required simply to maintain the current level of prediction accuracy. The third empirical study indicates that intra-individual variations become greater over time, implying the need for longer multiday periods of behavioral observation. Although these are just a small part of the empirical results of changes in travel behavior, the results clearly support Gifford's (2003) assertion: the assumption that travel demand is predictable over a 20-year planning horizon is no longer supportable. Particularly, implications from the empirical findings that activity–travel behavior has diversified over time are critical for travel demand forecasting. If prediction procedures cannot be improved, there is a possibility that uncertainty in demand forecasting will gradually increase. In the next section, we discuss several possible ways to improve transportation planning procedures.

11.5 Implications for Transportation Planning

The proper role of travel behavior analysis (particularly travel demand prediction) in the transportation planning process may depend on the degree of prediction accuracy (or uncertainties in prediction). If we could accurately estimate future travel demand, then we could depend more on travel behavior analysis, and vice versa. Some uncertainties will be reduced by improving behavioral observation and modeling techniques, while some will not. In this section, we first discuss the former aspect; that is, how we can reduce uncertainties by improving travel behavior analysis. We then discuss other components of transportation planning that could compensate for the imperfection of prediction. Finally, the implications for transport planning in developing countries are discussed.

11.5.1 Reducing Uncertainties by Improving Travel Behavior Analysis

The empirical results above indicate several ways to reduce uncertainties in travel behavior analysis. One important implication is that we have overlooked the importance of intraindividual variation (i.e., situational/contextual information) in the modeling of travel behavior analysis. In line with this view, a number of efforts have been made to collect multiday travel diary data (e.g., Pas 1986; Hanson and Huff 1988; Roorda et al. 2005; Axhausen et al. 2002, 2007; Hato and Kitamura 2008) and to develop more accurate activity–travel behavior models by incorporating a number of new aspects such as activity scheduling, household/social interactions, planned/unplanned activities and the psychological aspects of activity–travel decisions (Kitamura 1988; Axhausen and Gärling 1992; Supernak 1992; Harvey 1996; Kitamura et al. 1997; Bowman and Ben-Akiva 2001; Timmermans et al. 2001, 2002; Miller and Roorda 2003; Bhat et al. 2004; Arentze and Timmermans 2004; Auld and Mohammadian 2009). In addition, the empirical results showed that behavioral changes may occur frequently, implying the need to develop dynamic models to reflect such behavioral changes. Accordingly, several dynamic models have been developed in previous studies (e.g., Hensher 1988; Kitamura 1990; Goulias 1999; Thøgersen 2006). The data required for such dynamic modeling have also been corrected (e.g., Zumkeller 2009). Moreover, data fusion techniques (Stopher and Greaves 2007; Acharya et al. 2011) have some potential to connect detailed behavioral data with other time-series data to shed light on behavioral changes.

There is no doubt about the importance of the above-mentioned improvements in travel behavior analysis. On the other hand, the contributions to the transportation planning process are difficult to capture without knowing the extent to which uncertainties are reduced because of the improvement. In other words, in addition to improving behavioral observation and modeling techniques, researchers need to implement uncertainty analyses to embed the improved travel behavior analysis methods in the transportation planning process in an appropriate manner. For this purpose, Rasouli and Timmermans (2012) reviewed current uncertainty analyses in travel demand models and found a lack of comprehensive uncertainty analysis. Further empirical analysis of uncertainties in travel demand models is an important future research task.

11.5.2 Reducing Uncertainties by Improving Other Components of the Planning Process

Gifford (2003) pointed out several fallacies in current long-term transportation planning. In this section, we first introduce two that may be useful for discovering other techniques for overcoming uncertainty in the planning process. The first is the exogenous goal fallacy: long-term transport planning is often conducted with goals in mind, but these goals do not magically present themselves to planners. Once the goals are fixed, it is difficult to change them, although value judgments may change. Gifford (2003) pointed out that one of the sources of this fallacy is that planning has been conducted as a purely scientific enterprise. Given the social and cultural aspects of cities, regions, and nations, it is clear that planning is a kind of trans-science problem that cannot be fully resolved by a purely scientific approach (Weinberg 1972). In this sense, it may be better to consider planning based not only on the technology of reason (e.g., rational decisions based on cost–benefit analyses) but also on the technology of foolishness (taking action to learn what is not known) (March 1979). This learning-by-doing strategy may be particularly important in developing countries' planning, where only limited data and model techniques are available. We will discuss this point in detail in the next subsection. The second fallacy is the predictive modeling fallacy, which is the transportation planners' predisposition to rely on medium- to long-range forecasts. Although the degree of this fallacy may depend on improvements in travel behavior analysis, there are several intrinsic difficulties in prediction, such as changes in people's values and decisions on other matters that the planners cannot decide (Friend and Jessop 1976; Hall 1982).

To avoid these fallacies, Gifford (2003) had three ideas: control, flexibility, and adaptive discovery. Control is a technique that turns an unpredictable environment into a predictable one. For example, laws and regulations are the main methods of control. If a prediction is different from the actual outcome, we can modify the degree of regulation to reach a certain level. Flexibility is a technique that is pliable or responsive to (unexpected) changes. For example, bus may be a more flexible option than light rail transit, because it is easier to open, close and reroute the service. Adaptive discovery is a kind of learning by doing as mentioned above. Findings from previous projects can be embedded in the current project, findings from the current project can be reflected in the next project, and so forth. Actually, this third idea can be regarded as a governing system of the two former ideas: the idea of adaptive discovery provides a platform for adjusting control and flexibility measures sequentially through the learning process.

Although control and flexibility are important ideas, they should be applied in an appropriate way. Of course, excessive control (for example regulating people's mobility too much) may be impractical because of the difficulty in justifying the possible negative impacts on economic condition. Excessive flexibility may reduce the cost efficiency of investments. Thus, careful institutional arrangements are needed to manage the learning process properly, as a number of previous studies have mentioned (Friend and Jessop 1976; Flyvbjerg et al. 2003; Gifford 2003). On the other hand, although a number of studies have pointed out the conceptual importance of institutional arrangements, the methods, findings and lessons of previous projects are retained only by the people involved and have not been collected and sorted in a practical manner. In this sense, learning from other projects implemented even in other cities/countries may be crucial, as recent studies have mentioned (e.g., Dolowitz and Marsh 2000; Bulmer and Padgett 2004; Ison et al. 2011; Marsden et al. 2012). In this regard, Dolowitz and Marsh (2000) underscore the importance of looking at "the process by which knowledge of policies, administrative arrangements, institutions and ideas in one political system (past or present) is used in the development of policies, administrative arrangements, institutions and ideas in another political system". Furthermore, transportation researchers have recently discussed learning from other cities/countries' experiences; for example, in a special journal issue focusing on "Transferability of urban transport policy" (Ison et al. 2011). Enhancing such learning processes may be crucial for better transportation planning decisions under uncertainty.

11.5.3 Implications for Planning in Developing Countries

Although advanced modeling techniques can be applied in developing countries, there are several intrinsic limitations. First, data have not been gathered in developing countries. Advanced surveys such as longitudinal surveys could be conducted, but the low literacy rate of poor people, for example, makes such complicated surveys difficult. Moreover, even if there were sufficient data, the lack of human resources may cause difficulties in using the advanced prediction techniques. In addition, many developing countries have a unique public transit system—paratransit. Because paratransit provides a huge number of jobs as well as mobility for poor people, more care may be needed in interventions in public transit systems. In this sense, those transferring the planning techniques in developed countries to developing countries should consider paratransit as well as the different institutional arrangements. Thus, uncertainties in transportation planning in developing countries are expected to be greater than in developed countries.

Considering these aspects, it may be worth applying the concept of single- and double-loop learning, proposed by Argyris and Schon (1978). Single-loop learning may correspond to a learning process where control and flexibility measures are sequentially adjusted to developing countries' situations. For example, because the results of regulating paratransit are uncertain, such actions may require repeated modification based on the results of previous actions. On the other hand, double-loop learning may correspond to the process of learning about the planning organization itself (i.e., altering its governing values) and the development of people's ability to make better choices in the face of complexity and uncertainty. For example, after repeated modification of regulations for paratransit, the organization may learn the pros and cons of the regulations, reexamine and finally alter its governing values. These learning processes may be important, but we do not have sufficient knowledge of them in the context of transport planning. There are a number of discussions in other fields, including public sector management (e.g., Argyris 1992; Common 2004; Vare and Scott 2007; Krasny et al. 2010; Lundholm and Plummer 2010; Sterling 2010). Learning from these existing studies for better capacity building may be important for improving transportation planning processes in developing countries.

11.6 Conclusions

This chapter has investigated uncertainty in travel behavior and its implications for transportation planning. Based on our empirical studies, we pointed out the intrinsic limitations and the importance of uncertainty analysis in transportation demand forecasting. In particular, developing more sophisticated demand models often only emphasizes the improvement of the existing models, and the extent to which uncertainty can be reduced using the refined model has not been well examined. For example, although a more sophisticated model may produce better goodness of fit, sometimes it may also reduce the temporal stability of the model. Thus, a comprehensive uncertainty analysis is needed before replacing an existing model with a newly developed model. Additionally, the proper role of demand forecasting in the transportation planning process may depend on the degree of prediction accuracy. If we could accurately estimate future travel demand, then we could depend more on travel behavior analysis, and vice versa. For this reason, uncertainty analysis in demand prediction is also crucial when we attempt to embed demand forecasting in the transportation planning process.

Considering the difficulty of completely eliminating uncertainties, we have also discussed other ways to improve transportation planning. Although control and flexibility could be significant measures in transportation planning under the existence of uncertainty, we have underscored the importance of learning mechanisms, partly because it could play a significant role in adjusting control and flexibility measures sequentially. In general, there are two types of learning mechanism: learning from experience accumulated in other countries/cities, and learning by doing; that is, learning from one's own experience. Recently, the importance of learning from other countries/cities has been underscored, mainly in Western countries. This type of learning may be effective partly because Western countries/cities tend to have similar attributes such as social and physical infrastructure, cultures, politics, societies and economies. Because a number of transportation policies lead to irreversible consequences, there are certain limitations on the implementation of trial and error experiments in some countries or cities. Thus, it would be better to learn from accumulated experience in other countries/cities. On the other hand, there is some difficulty in doing so, especially regarding some developing countries/cities, mainly for the following reasons. First, developing countries often have a unique public transit system, and thus it may be less efficient for them to learn from Western countries' experiences than it is for Western countries to learn from each other. Second, even where countries/cities have similar properties in terms of features such as their social and physical infrastructure and economies, information about their experiences is not well organized. Under such conditions, learning-by-doing processes may play a significant role in developing countries' transportation planning process.

Research on uncertainties in transportation planning may not be just a theoretical or conceptual research theme but also quite a practical one. For example, it should address the possibility of the failure of assumptions in demand forecasting and the extent to which we should believe that prediction results are important practical issues affecting administrative and institutional arrangements for planning. Kouvelis and Yu (1997) noted that the best way to handle uncertainty is "to accept uncertainty, make a strong effort to structure it and understand it, and finally, make it part of the decision making". To do this, experiences in various countries/cities should be described and shared, including the failure of demand predictions and policy implementation. Experiences of failure, in particular, may be shared less frequently, presumably because people may fear blame. In such cases, however, we lose opportunities to learn from the failure and to avoid repeating it in another context, resulting in an inefficient learning cycle. The underlying cause of this may be a lack of understanding of the nature of uncertainty in transportation planning: it cannot be eliminated perfectly, and thus there is always a possibility of failure. For this reason, it would be beneficial to understand the danger of criticisms such as "demand forecasting should never fail," and as a first step, we may have to accept that inescapable uncertainties exist in the planning process, at least in current practical planning procedures. Further conceptual, theoretical, and empirical studies are certainly needed to deepen our understanding of the nature of uncertainties in transportation planning.

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