Christoph Breidert

Estimation of Willingness-to-Pay

Theory, Measurement, Application

DUV GABLER EDITION WISSENSCHAFT

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With a foreword by Prof. Dr. Thomas Reutterer

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To my parents

Foreword

The work of Christoph Breidert is positioned in a methodologically challenging area of marketing research that is highly relevant to both theoretical investigations and practical applications.

Determination of willingness-to-pay for products and/or services from a customers perspective is crucial for modern approaches to pricing decision-making. Based on the increasing availability of individual transaction data (e.g., scanner data, consumer panel data, and data from Smart Cards) remarkable improvements have been achieved in estimating advanced price response models based on observed purchase data. However, empirical price and/or product variations are typically very limited in such historical data which complicates accurate willingness-to-pay estimation or makes it even impractical. This is especially true when entirely new products are planned to be introduced or alternative marketing strategies (e.g., product bundling) are considered by the management. While asking customers directly for their willingness or unwillingness to purchase a specific product at the designated price commonly results in unrealistic estimates, experimental survey-based methods turned out to be a promising approach for the indirect measurement of willingness-to-pay. Among the most prominent techniques within this methodological framework is conjoint (or trade-off) analysis, which aims at inferring respondents preference structures based on their reactions to systematically varied profiles of product attributes (mostly including price) in an experimental design.

In his work, Christoph Breidert provides a systematic overview of the competing methods that have been and are still applied in todays practical and theoretical pricing research. He then narrows his focus on a detailed discussion of the efficiency of different conjoint measurement techniques with respect to their capability to estimate willingness-to-pay at the individual level. After identification of several candidate approaches he recognizes their specific merits and discusses obstacles and open issues regarding their adoption to measuring willingness-to-pay.

Keeping the previously identified drawbacks of traditional methodology clearly in mind, Christoph Breidert proposes an innovative conjoint-based technique to estimate an individual consumers willingness-to-pay. The basic idea behind this novel approach is to unlink inference of respondents non-price product preferences from the estimation of price response behavior. This is accomplished by an additional interview scene appended to conventional conjoint measurement. While price is excluded from the conjoint tasks, the latter stage is responsible for estimating the exchange rate between conjoint part-worths and willingness-to-pay.

The empirical performance of this new approach is demonstrated using an application study in the area of product bundling for mobile telecommunication devices. Furthermore, it is shown that simulations of the estimated individual level prices make the expected response behavior to different bundling scenarios accessible and thus provide viable information for the identification of promising cross- and up-selling strategies.

By critically reviewing existing methods for estimating willingness-to-pay and by rigorously backing up his research from a methodological perspective, Christoph Breidert has developed both an innovative approach and a promising procedure to advance the process of decision-making in modern price management. It was a pleasure to me to escort the emergence of this contribution and I am confident that the audience will appreciate this interesting piece of work as well.

Thomas Reutterer
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Vienna University of Economics and Business Administration

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As is expected with an endeavor of this scale, there are numerous people who have helped to make it possible and worthwhile. I would like to take this opportunity to thank them.

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A special thanks goes to Dr. Michael Hahsler of the Department of Information Business who was not only my mentor but a great colleague throughout my doctoral studies. In this time we had many challenging conversations, and he guided me in my research, providing extensive practical advice regarding execution of my research. To him I am greatly indebted for all his support.

Likewise, I would like to thank Prof. Dr. Dr. Lars Schmidt-Thieme for providing me the software I used in the empirical investigation of this dissertation.

I would also like to thank all the wonderful colleagues I met at the Department of Information Business throughout my doctoral studies. Especially Christian Neumann with whom I shared the office throughout this time, thanks it was great.

Christoph Breidert

Table of Contents

List of Figures

List of Tables

Glossary

ACA	Adaptive conjoint analysis
ACP-12E	Nokia battery charger
ANOVA	Analysis of variance
BDM	Becker, DeGroot and Marshak procedure
CBC	Choice based onjoint
cf.	Compare (Latin: confer)
CNT-327	Nokia leather bag for mobile phones
DCV-14	Nokia battery charger
DKU-2	Nokia data cable
DKU-5	Nokia data cable
DVD	Digital versatile disc
e-mail	Electronic mail
e.g.	For example, for instance (Latin: exempli gratia)
Ed.	Editor
Eds.	Editors
et al.	And others (Latin: et alii)
FM	Frequency modulation
HB	Hierarchical bayes
HDS-10	Nokia headset
HDW-2	Nokia headset
HS-2R	Nokia radio headset
HS-5	Nokia headset
HTML	Hyper text markup language
i.e.	That is to say, in other words (Latin: id est)
jAC	Java adaptive conjoint
LCH-12	Nokia charger cable for use in cars
MBA	Master of business administration

MBC-15S	Nokia hands-free speaking system for use in cars
MCMC	Monte carlo Markov chain
MONANOVA	Monotone analysis of variance
N-Gage	Nokia mobile telephone and gaming device
NOKIA 3220	Nokia mobile telephone
NOKIA 5140	Nokia mobile telephone
NOKIA 6220	Nokia mobile telephone
OLS	Ordinary least squares
PDA	Personal digital assistant
PE	Scene Price estimation scene
WTP	Willingness-to-pay

Chapter 1

Introduction

1.1 Research Intention

Setting the right price for a product or service is one of the hardest things for a marketer. In many cases the perception of a product or service by the customers is the cornerstone to successful pricing. Unexploited diversification and pricing potentials are often the main driving forces for dramatic price developments and the origin for diversified product offerings.

An outstanding example is the formation of low-cost (or no-frill) airlines in Europe after the liberalization of the European domestic aviation market was completed in 1997. By the year 2002 low-cost airlines had gained substantial market shares. Furthermore, low-cost carriers are expected to increase their market share in the coming years as can be seen in Figure 1.1. Airlines such as Ryanair, EasyJet, and GO penetrated the market with aggressive pricing strategies putting the established airlines under pressure. Unlike established airlines, low-cost carriers offer little service on board (no frills), have higher seat closeness, accept only direct booking, use cheap secondary airports, do not offer flexibility on cancellations, and have enticingly low fares that rise only as a flight fill up.[1]

However, many flight customers prefer the reduced prices over additional service and convenience as offered by established airlines and use no-frill flights instead. The aviation market had a great unexploited potential which was not recognized by the established airlines. With the new low cost alternative to traditional flying many passengers have switched to the low-cost offerings, and new customers have entered the market that did not fly so frequently previously.

The aviation example shows how important pricing is when a new business model is implemented. Recognizing unexploited segments in a market is the key for designing a marketing strategy. To make the right strategic decisions marketers need valid instruments to estimate the preference structure of their customers. With such instruments they must be able to forecast market response when existing marketing strategies are changed or new marketing strategies are initiated.

[1] "Turbulent skies". (2004, July 10). Economist.

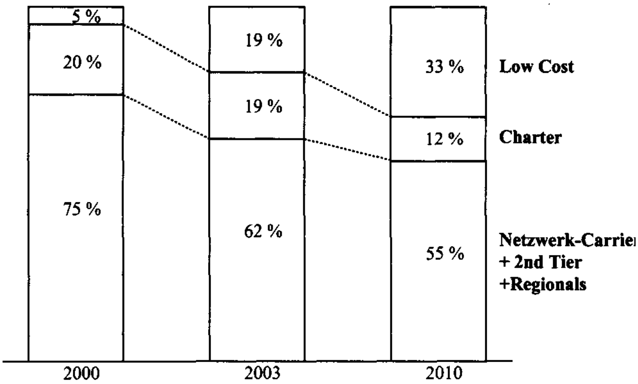


Figure 1.1: Market shares in the European aviation market in terms of percent passengers ("Impact of Low Cost Airlines - Mercer Study", Mercer Management Consulting, 2004).

Examples of such marketing strategies are the differentiation or diversification of existing products, along with the introduction of new products. Product differentiation is the modification of a product to make it more attractive by differentiating it from competitors' products. Product diversification means providing different types of an existing product to better serve different customer segments. Low-cost airlines entered the aviation market with a differentiation strategy.

Following the daily news other interesting examples can found in the mobile phone industry. Mobile phones have changed dramatically over the last years. In the past mobile phones were un-stylish, uncomfortably large and heavy, had small monochrome screens and large antennas, and were only used for one thing: talking to other people.

Today's latest models, are elegantly shaped pocket computers with high resolution color screens. And in contrast to previous years mobile phones have become a uniquely personal item. Some phones designed for business users provide office functionalities, have tiny keyboards, and are capable of sending an receiving e-mails in addition to text and multimedia messaging. Other phones have satellite-positioning functions, high-resolution cameras that take pictures and record and play video clips, have a music player, FM radio, and can function as a game console. The mobile phone has become such an important aspect of a user's daily life that it has changed from being a mere 'technological object' to a key 'social object' (Srivastava, 2005).

Mobile phones are sold to a large number of consumers that have heterogeneous needs and requirements. Diversified phones are offered in all price classes, and the mayor mobile phone companies Nokia, Motorola, Samsung, and Sony Ericsson offer product lines with many different telephones.

The mobile phone industry has experienced a huge growth over the past years. In 2003 the number of mobile phones in use worldwide was around 1.4 billion overtaking the number

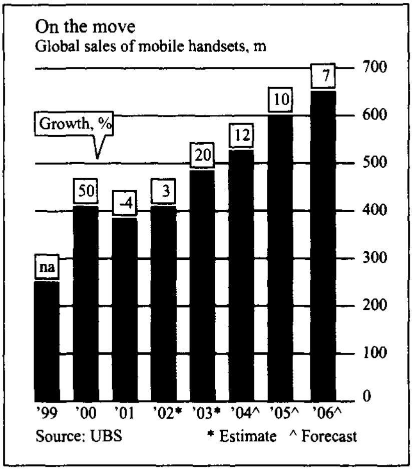


Figure 1.2: Growth of global sales of mobile phones ("Battling for the palm of your hand - Mobile phones", Economist 2004, April 29th).

of fixed-line phones. As illustrated in Figure 1.2, more than half a billion mobile phones are sold every year. In 2004 mobile phone sales hit 683 million. This is an increase of 32% from the sales in 2003.[2]

Nokia, the number one manufacturer of mobile phones had a share of 30% of the overall cell phone market in 2004. However, Nokia had to cut prices in order to stem market share losses. Those price cuts have impacted profits, and for the year 2004 Nokia reported a decrease in operating profit by 14% to € 4.330 million (€ 5.011 million in 2003).[3]

It can easily be seen, that in the mobile phone market well planned marketing strategies must be used, in order to best meet the different demand types in the market. Nokia is doing its best to diversify, most notably into mobile gaming with its N-Gage handset, which was released in fall 2003. Tracking down new trends and adapting to changing consumer preferences is very important in order to consequently diversify the companies' product line.

Even more important than keeping track of consumer preferences marketers must be able to forecast the reaction to different pricing strategies. The Nokia N-Gage currently costs 229,- €.[4] Is this a good price or is there unexploited market potential?

Huge profits gains can be realized with a clever pricing strategy, and sever profit losses

[2] "Slower Growth Seen In '05 For Mobile Phone Industry" (2005, January 27th). Investors Business Daily.

[3] Nokia Press Release (2005, January 27th), http://www.nokia.com/results2004Q4e.pdf, visited February 5th, 2005.

[4] Retail price in http://www.nokia-online-shop.de, visited February 5th, 2005.

can be avoided. Pricing is the most important element of the marketing mix because "price is the only marketing strategy variable that directly generates income. All the other variables in the marketing mix generate costs: advertising and promotion, product development, selling effort, distribution, packaging – all involve expenditures" (Monroe, 2003, p. 8). Furthermore, the price for a product is the marketing variable that can most easily be adjusted. Even a small difference in price can have a determining impact on the success of a marketing strategy.

This dissertation is about methods to estimate consumers' preference structure and reactions to different prices. We show by discussion, review of literature, and simulation with real consumers, how different methods can be applied to forecast consumers' response behavior when they are confronted with varying products at ranging prices.

The best way to forecast market response is to perform experiments with different product configurations. The reaction of the probands can be used as a predictor for the behavior of the whole market. However, experiments depend heavily on whether the participants can be chosen such that customer population of the target market is represented. Furthermore, the experimental setup must closely mimic real market behavior. Experiments that meet these requirements can be quite costly and time-consuming and are therefore not always feasible (Nagle and Holden, 2002, p. 339-342).

Instead, a marketer needs a set of instruments to quickly estimate consumer behavior. In order to use these instruments frequently they must be reasonable costly, easy to use, and be applicable in a broad variety of market scenarios. If experiments cannot be used, marketers must rely on surveying techniques. Therefore, the focus in this dissertation is laid on surveying techniques to estimate customer reactions to different product offerings. Different surveying techniques are discussed theoretically and by example and advantages and disadvantages are emphasized.

One fundamental differentiation criterion for surveying techniques is that some estimate price response behavior at the individual level and others at sample level. If the preference structure of the members of a sample is very heterogeneous, response behavior at sample level only represents a small fraction of the individuals. The number of customers who actually have the predicted response behavior cannot be forecasted, and potentially more homogeneous segments cannot be identified. For heterogeneous consumer markets individual level surveying techniques are better suited, because sample heterogeneity and possibly more homogeneous smaller segments can be recognized.

Another important property of surveying techniques is given by whether purchase behavior is hypothesized or actually surveyed during the interview. Conjoint analysis, for example, is a surveying technique that estimates preference structure but not choice behavior. Estimating preference structure means, that for different competing products it can be predicted which one is the most attractive, but it cannot be predicted whether the most attractive product would actually be purchased. To avoid this problem marketers usually assume a status quo product and hypothesize that every member of the sample would purchase this product. Against the status quo product new or differentiated products are tested.

When purchase behavior is ex-ante hypothesized, market expansion and contraction effects at different prices cannot be predicted. Furthermore, a strong hypothesis about price response behavior can be a great source of error.

Another method that is often used in pricing studies is discrete choice analysis which is also referred to as choice based conjoint (CBC). In contrast to regular conjoint analysis this surveying technique actually elicits choice behavior. During the interview the respondents are asked to indicate whether they would purchase a product at a given price. However, discrete choice analysis estimates consumer behavior at the aggregate level.

In the discussion of surveying techniques used in pricing studies we stress the drawbacks of conjoint analysis and discrete choice analysis. Besides the strong status quo product hypothesis conjoint analysis has another problem: When a pricing study is carried out by means of conjoint analysis, it is normal that the price is included in the interview as yet another attribute. This dissertation outlines problems that can arise from the inclusion of price as an attribute. Discrete choice analysis does not suffer from these problems. The drawback with discrete choice analysis is that price response behavior is not estimated at the individual level. As described above, this can lead to several problems when the degree of heterogeneity of the target market is unknown.

In view of existing methods we show that there is an instrument missing that estimates price response behavior at the individual level and has the ability to elicit choice behavior. We have developed such a new instrument. Firstly, it performs all estimations at the individual level, and secondly it explicitly elicits price response behavior. This new method is the main contribution of this dissertation.

The new method is a combination of conjoint analysis with an additional interview scene in which choice behavior is surveyed. The additional interview scene is called *Price Estimation scene* (PE scene).

In order to get estimates at the individual level conjoint analysis is the most powerful approach as illustrated by its numerous applications in the past 30 years. For overviews see Wittink and Cattin (1989), Wittink and Burhenne (1994), Baier (1999), Voeth (1999), and Hartmann and Sattler (2002a,b). Therefore, a conjoint approach is useful if individual level preference data is to be elicited.

In the preceding conjoint analysis price is not included as an attribute as is usually done in pricing studies with conjoint analysis. For each individual of the sample his or her preference structure is only estimated for the non-price attributes. Price enters the interview in the following PE scene. In this scene price response behavior is then explicitly elicited by presenting the individual different choice scenes. In each of these scenes a product profile of the conjoint study is dynamically selected. The product profile is assigned a price, and the respondent is asked to indicate whether he or she would buy that profile at the given price. The PE scene is different for every respondent because it depends on the preference structure estimated in the preceding conjoint analysis. Furthermore, the sequence of choice scenes and the prices are adapted for each individual based upon his or her choice behavior.

Our new method was tested in an empirical study with the customers of the online-shop of Nokia in Germany. At the time of the study the shop was offering telephones with contracts bundled together with suitable telephone accessories at discounted prices. In the empirical study simulations with these product bundles and varying telephone accessories were performed. It shows that the simulations can be used to design bundling strategies for different product bundles. The benefit of bundling is that the heterogeneity of the demand in the market is reduced, when customers with heterogeneous tastes switch from single purchases to buying a bundle.

Estimating response behavior to different bundles for a heterogeneous customer base is a very challenging task for a marketer and difficult questions are raised: Which of the many possible bundles should be offered for sale? Should more than one bundle be offered simultaneously? What are the best prices for the bundles? Should the components of the bundles also be offered for single sales, or should they just be offered as a bundle? These questions can be answered using the PE scene and performing simulations based on the individual level price response estimations.

To gather the data an online survey was performed. It was realized as an adaptive conjoint analysis (ACA) to which the PE scene was appended. The results of the simulations for different bundle types of which some were actually offered in the online shop are presented in this dissertation. The offerings of different single bundles and the simultaneous offering of many bundles was simulated. Furthermore, the effect of the presence or absence of single sales was investigated. Based upon the simulations we show how different pricing strategies affect sales and profits. The performed simulations are only possible based upon elicited individual level price response behavior.

1.2 Structure of the Thesis

In Chapter 2 the reader is introduced to the role of pricing in the marketing mix. By discussing recent developments in marketing it can be seen that pricing has turned from cost oriented approaches to value based approaches. In value based approaches a marketer estimates the perceived values of a product and sets a price in view of these valuations. In cost based approaches the price of a product is primarily set in view of the costs. In order to apply a value based approach the marketers need estimates for the valuations the customers have for different product offerings. After the introduction to value based pricing, its importance will be demonstrated by discussing practical applications published in scientific journals. After this discussion we will focus on product bundling which is a special type of pricing strategy. We give the reader an introduction to bundling because different bundling strategies will be simulated in the empirical investigation.

Chapter 3 introduces different concepts, by which customer reactions to price are determined. The concepts investigated are the *reservation price* and the *maximum price*. Both concepts subsume under the term willingness-to-pay (WTP). Although the concepts are sometimes used synonymously, in this incidence there will be a distinction between the two. This distinction is important for the discussion of different estimation procedures and for the development of our new surveying procedure, the PE scene.

Chapter 4 provides an overview and critical discussion of state of the art instruments marketers use to estimate price response behavior. By discussing advantages and drawbacks of each of the techniques, it will be argued that a new method is needed by which willingness-to-pay can be estimated at the individual level that does not rely on an ex-post hypothesis about purchase behavior.

In Chapter 5 an introduction to conjoint analysis is offered, as the PE scene is an extension of conjoint analysis. A focus is laid on the relevant parts of conjoint analysis to the new method. Furthermore, an introduction to the software used will be given.

Chapter 6 illustrates the importance of conjoint analysis in pricing studies by providing an overview of selected publications. Based upon these articles it is intended to show the strengths and weaknesses of the existing approaches. Focusing on the effects that arise from including price as yet another attribute in a conjoint study a number of arguments, why the inclusion of price in a conjoint study is problematic, will be presented. These arguments heavily influenced the design of the PE scene, which is based on a conjoint analysis that does not have price included as an attribute.

In Chapter 7 the PE scene is developed. The underlying techniques to select product profiles individually for each respondent are discussed, and the price selection mechanism is introduced. Furthermore a discussion regarding the derivation of estimates of the respondents' WTPs for all possible product combinations that can be formed from the attributes and levels of the conjoint analysis is given. Illustrative screenshots are presented as well as sample results.

In Chapter 8 the empirical study with the customers of the Nokia online shop in Germany will be presented. Simulations for different bundle types were performed. Some of the bundles for which willingness-to-pay was estimated were actually offered in the online shop at the time of the study. For a selection of different bundles price response behavior at different prices were simulated. Additionally, the impact of the marketing strategies pure-bundling and mixed-bundling was simulated. Based upon these simulations different effects are presented and discussed, such as cannibalization effects and market expansion and contraction.

In Chapter 9 the main findings and results are summarized and an outlook to future research is provided.

Chapter 2

Pricing in the Marketing Mix

In this chapter the role of pricing in the marketing mix is examined. An emphasis is placed on its importance and sample applications from the literature in which pricing strategies were developed alongside with the development of a marketing strategy are present. The main objective of this is to familiarize the reader with pricing research in the context of marketing. The importance of pricing also explains the great interest in the topic the management of the Nokia online shop in Germany has.

It will be shown that pricing has turned from cost oriented approaches to value based approaches. In value based approaches a marketer estimates the perceived values of a product and sets a price in view of these valuations. This is an important development because in order to estimate consumers' valuations for different product offerings a marketer needs reliable instruments for estimation.

Subsequent to the discussion regarding the role of pricing in the marketing-mix the next focus is on bundling strategies. Bundling is a special type of pricing strategy. Different types of bundling and underlying mechanisms will be introduced as simulations of different bundling strategies are part of the empirical investigation of this thesis, which will be presented in Chapter 8.

2.1 The Role of Pricing

Pricing is one of the most important elements of the marketing mix (Nagle and Holden (2002, p. 13), Monroe (2003, p. 8)). It is the only element that generates income. All other elements, such as advertising and promotion, product development, selling effort, distribution, packaging and so forth, involve expenditures. The price at which a product is finally offered interacts heavily with most other elements of the marketing mix. Setting the "right" price for a product or service is the number-one problem facing many marketing executives.

There exist many definitions of price in literature. Kotler and Armstrong (2001, p. 371) define price as "the amount of money charged for a product or service, or the sum of the values that consumers exchange for the benefits of having or using the product or service".

Cost-Based Pricing								
Product	$\longrightarrow$	Cost	$\longrightarrow$	Price	$\longrightarrow$	Value	$\longrightarrow$	Customers
Value-Based Pricing								
Customers	$\longrightarrow$	Value	$\longrightarrow$	Price	$\longrightarrow$	Cost	$\longrightarrow$	Product

Figure 2.1: Cost-Based versus Value-Based Pricing (Nagle and Holden, 2002, p. 4).

Monroe (2003, p. 5) defines price more formally as

$$P = \frac{M}{G}$$

with

P	:	Price
M	:	Quantity of money or goods and services received by the seller
G	:	Quantity of goods and services received by the buyer.

To employ a good pricing strategy for products a company needs good estimates of the amount of money customers are willing to pay for the offered products. In practice many firms still do not apply sufficient pricing strategies for their products (Monroe, 2003, p. 19). Among many possible mistakes in pricing decisions pricing is often too cost oriented, rather than being based on the values of the products as perceived by the customers. Another source of foregone profit is too little product differentiation. Product differentiation is the modification of a product to make it more attractive to a certain group of customers differentiating it from competitors' products. Differentiation aims at dividing the customers into segments and optimizing the products for the specific needs of the segments. Differentiation requires a sophisticated pricing strategy based on the perceived values of the products (Kotler and Armstrong, 2001, p. 371).

Mostly, the pricing of a product is placed inside a marketing strategy at a higher level, such as a skimming or penetration strategy. This strategy determines the surrounding factors for pricing. Within a defined strategy a firm may wish to seek short-term objectives for a single or a family of products. Among the most common objectives is profit maximization of the current product, or increase of market share. Both objectives rely on thorough knowledge of how the market will react to different pricing patterns. For such short-term objectives price is the most important element. It is the most flexible element of the marketing mix. It can be changed and adjusted quickly and short term adjustments translate directly into changes in profit and market shares.

Many companies base their prices for products on the consumers' perceived values. This approach is called *value-based pricing*. In contrast to *cost-based pricing* marketers do not design a product and marketing program and then set the price. Rather, price is considered along with the other marketing variables before the marketing program is set.

The company estimates the perceived value of the product which is to price. Based on the target value and target price the decisions about the design of the product and the costs can be incurred (Kotler and Armstrong, 2001, p. 386). The difference between the two procedures is shown in Figure 2.1. Orienting pricing decisions towards value rather than basing them on costs if more difficult, but the profit potential for having a working value-oriented pricing strategy is far greater than with any other pricing approach (Monroe, 2003, p. 192). On the other hand poor profits because of misinterpretations of the consumers' valuations are also possible. If the anticipation of the perceived value is too high, and prices are set too high accordingly, the sales of the company will suffer. If the products are underpriced, they produce less revenue.

Taking an orientation towards value indicates recognition that preferences of customers are not constant but rather change (Monroe, 2003, p. 192). For developing a pricing strategy based on value companies need to estimate the currently perceived values of their products. In practice most firms attempt to measure the demand for their products directly at different prices based upon historical sales data. This does not always lead to the wanted results, because the demand often depends on the competitors' prices. Additionally, there exist other elements in the marketing mix that affect the demand, for example an increase in advertising, or external effects such as holiday weekends. When the demand for different products at different price levels is estimated based on historical sales data, the marketer must be sure that all influencing effects on the sales data do not vary. This proves to be difficult in competitive markets and is often not feasible (Kotler and Armstrong, 2001, p. 381).

Therefore, marketers need to rely on other techniques. A thorough discussion of value estimation techniques will be given in Chapter 4. At this point it is only necessary to emphasize the importance of the knowledge of the values that customers currently attach to products. This knowledge is substantial in order to develop a sophisticated pricing strategy.

When a company introduces new products, different pricing strategies can be adopted. If a single product is launched, this can either be a skimming or a penetration strategy. Adopting a skimming strategy means charging a relatively high price for a short time for the new innovative, or much-improved product. A penetration strategy involves setting a lower price in order to achieve a large market share. When a new product is introduced in combination with other new products or in the presence of existing products, a product-mix strategy is applied. Kotler and Armstrong (2001, p. 401) identify five product-mix pricing strategies which are presented in Figure 2.1. All strategies target different customer segments and rely heavily on correctly identifying the values customers attach to the products the company offers.

2.2 Sample Applications of Pricing Studies

One of the techniques used to estimate the perceived value customers attach to products is conjoint analysis. The method will be introduced in detail in Chapter 5. In this section

Strategy	**Description**
Product line pricing	Setting price steps between product line items
Optional-product pricing	Pricing optional or accessory products sold with the main product
Captive-product pricing	Pricing products that must be used with the main product
By-product pricing	Pricing low-value by-products to get rid of them
Product bundle pricing	Pricing bundles of products sold together

Table 2.1: Product-mix pricing strategies (Kotler and Armstrong, 2001, p. 401).

some selected cases in which researchers have attempted to develop a pricing strategy based on perceived values are introduced. The cases presented estimate perceived values by conjoint analysis. The context in which conjoint analysis has been applied with respect to price ranges from product pricing, product/concept evaluation, product repositioning, competitive analysis of products, to market segmentation (Green and Srinivasan, 1990).

The first example for estimation of perceived values is in the context of evaluation of "really" new products. With really new products no competing products exist, and the demand for them is created when the product is introduced. To understand the importance of different features and to develop a pricing strategy for such products conjoint analysis can be applied. Green et al. (1997) used conjoint analysis to evaluate different concepts for electronic toll collection in regional transportation in the New York - New Jersey area. At this point there existed no such system, and the potential customers had little experience with electronic toll collection. With the study Green et al. managed to identify the key aspects of the system of which one was price. With the study the authors estimated the perceived values the participants attached to the usage of different electronic toll collection systems. Based upon these findings market forecasts were performed and the system was designed and successfully introduced.

The second example is the repositioning of a pricing strategy for subscriptions to a performing arts series. Currim et al. (1981) performed a conjoint analysis to test the impact of different factors on subscriptions for a performing arts series. It was planned to offer events bundled together in package subscriptions. Important questions among others were how to set the discounted price for package sales and the price for single tickets. Statistical analysis of historical data did not provide the necessary variable variations to address the outlined questions. Experimenting with prices was also not possible, because the performing arts organization served only a regional geographic area, and thus were concerned with potential ill-will if different customers from the same audience were sold the same subscriptions at different prices. In addition to the conjoint study the respondents were ask to provide information about their income. Based upon this information the respondents were segmented. The study showed that the importance for price varied for the different customers segments. With higher income the importance of price decreased, and other factors such as prestige of actors became more important. Also, the importance of package discount decreased for higher income segments. The study clearly indicated the importance of a diversified pricing strategy for different customer segments. "The challenge is to develop a strategy that responds to the price and discount indifference of the high-income groups and the sensitivity of others" (Currim et al., 1981). Thorough knowledge is needed of the size of the segments and estimates of willingness-to-pay for tickets and packages in the different segments. Based upon estimates of the preference structure and willingness-to-pay the marketing mix of the performing arts organization was optimized, and sales and profits could be increased.

The third example is a pricing study carried out by Green and Krieger (1992) to estimate the effect of the repositioning of a pharmaceutical firms medical treatment product used in hospitals. The pharmaceutical firm's product competes with two similar products and holds a market share of about 29%. 365 conjoint interviews were performed with responsible personnel of different hospitals. The conjoint study consisted of the product's relevant attributes and varying cost levels for patient treatment. Based upon the elicited data the analysts were able to estimate the profit per single treatment under an optimal product design (with an optimal price), assuming that the competitors held their product profiles constant. Second, under the same assumptions the authors optimized a product that would yield the highest market share. Third, another option was the introduction of a new differentiated product besides the existing product. Market shares and profits for this option were also estimated. With the estimation of the price response behavior to different product configurations a successful repositioning strategy could be implemented. Based upon their findings Green and Krieger (1992) point out the four most important issues in product positioning and pricing:

1. Estimation of market shares for different product configurations.
2. Optimization of product configurations under profit-return aspects.
3. Identification of customer segments.
4. Estimation of cannibalization effects.

A fourth example is the development of telephone tariffs (Eggenberger and Christof, 1996). In view of the liberalization of the telephone market planned by the European Union for 1998, the authors point out that the market would turn towards a buyer's market. Therefore it is important for new entrants to have estimations of preference structure of all participants in the market. Eggenberger and Christof analyze relevant factors for telephone tariffs in a liberalized telephone market by adaptive conjoint analysis. The two most important factors are availability and price. Based upon the analyzed factors the authors were able to segment the respondents of their interview in four clusters. Each of the clusters had a different preference structure. Based upon the data they were able to perform market forecasts under different scenarios. They suggest that a new telephone provider should pay attention to the two most important factors: Price and availability. In addition designing a marketing strategy for the business segment, the provider should especially design products for different customer segments.

Another example for the estimation of perceived values in the context of new product introduction is found in an article by Mahajan et al. (1982). For new product introductions the authors emphasize the importance of estimating price demand curves for penetrating existing markets as well as for developing markets. The authors perform a conjoint study testing different brands of consumer nondurable goods at different prices.

Balderjahn (1991) applied conjoint analysis to estimate price response functions for personal computers. The market share of a new computer under different pricing schedules was estimated, while the competing computers were held constant in price.

The list of sample applications published in scientific journals could be continued here. However, we do not wish to present a comprehensive overview of possible applications, but rather attempt to show the important impact that value estimation techniques play in designing a marketing strategy in the literature as well as in practical applications.

2.3 Product Bundling

This section focuses on a special form of product differentiation, known as product bundling. In product bundling products are grouped together for joint sales. Different bundles as well as the unbundled products can be differentiated by suitable pricing strategies aimed at the customers' valuations for the different offerings. As later in Chapter 8 an empirical study on bundling will be discussed, this type of pricing strategy is thoroughly studied here.

Product bundling is used in many fields of retailing. Well known examples are found in the fast-food industry. Restaurants like McDonald's, Burger King, and Pizza Hut group food together as menus. In the software industry this is a common phenomenon as well. For many years Microsoft has adopted this strategy. Different programs for text processing, spread sheets, and presentation are sold together as MS Office. Other fields are the tourism and the services industry, and so forth. See Wübker (1999) or Simon and Wübker (1999, pp.18-21) for more applications.

A bundling strategy can be used for product repositioning or product differentiation. The former is the altering of an existing product to make it more appealing to the market place. In the latter one or more attributes of an existing product are modified to make it different from others. Bundling an existing product together with additional features or services can serve as a repositioning or differentiation strategy. In view of this Eppen et al. (1991) suggest that bundles should be treated as new products.

Generally, bundling can be used for the introduction of new products bundled together with existing products. An example for this is given in Simonin and Ruth (1995). The authors perform a study to test for willingness-to-pay for a new product bundled together with different tie-in products. They find that the valuation of the tie-in product affects the valuation of the new product.

Product bundling has also been applied to the distribution of information goods, for example newspaper articles, music, photographs, video clips, stock quotes, research reports, and so forth. A discussion on bundling of information goods can be found in Varian (1995), Bakos and Brynjolfsson (1999a), Bakos and Brynjolfsson (1999b), and Kephart et al. (2001). Bundling information goods is a special case of bundling because these goods typically do not have variable costs. Only fixed costs for the initial production of the goods occur. Since variable costs can be neglected, very large bundles can be offered, for example all video clips in contrast to a selected subset of video clips. However, the dynamics underlying these bundling strategies differ from the dynamics of physical goods. For this reason, they are not of interest in this dissertation and will not be considered in the following.

The primary benefit of product bundling lies in the segmentation abilities, by which consumer surplus can be extracted more effectively (Schmalensee (1984), Olderog and Skiera (2000)). In marketing research bundling is often described as a form of price discrimination. The most often cited taxonomy of price discrimination is found in Pigou (1920, pp. 275). In this taxonomy three levels of discrimination exist.

First-degree price discrimination is also referred to as perfect price discrimination. It means that the supplier of some product can sell it to every customer at a different price. Prices for different units of the product can also be varied from customer to customer.

Second-degree price discrimination means that the supplier sells different units of a product for different prices. But every customer who buys the same amount of the product pays the same price. Thus, the price depends on the amount of the product purchased. In contrast to first-degree price discrimination it does not depend on who does the purchasing. Volume discounts are a common example of this sort of pricing.

Third-degree price discrimination occurs when the supplier sells some product to different customers groups or segments at different prices. But every unit of the product sold to a group sells for the same price. This is the most common form of price discrimination. Examples of this include student discounts, senior citizen's discounts, and so forth. The difference between second- and third-degree price discrimination lies in the objective, which the differentiation is aimed at. In the former case the differentiation is based on properties of the products, in the latter case on properties of the consumers.

As will be argued in the following, product bundling is a form of price discrimination of the third degree. Price discrimination under product bundling depends on how much the different customers are willing to pay. Under different product bundling strategies, customers self-select into segments based upon this property.

For illustration of the underlying mechanism of product bundling we follow the well known model of Adams and Yellen (1976). In this simple model two products are bundled together. Suppose two products X and Y are offered for sale. The two products do not depend on each other. Furthermore, a market with only one vendor of the products is assumed and reselling of goods is prohibited. The vendor attempts to maximize her profit. In such a monopolistic scenario the vendor can apply different bundling strategies. The strategies we consider here are *pure-unbundling*, *pure-bundling*, and *mixed-bundling*. Under pure-unbundling the products are only sold separately. Under pure-bundling the products X and Y are only sold bundled together as one offering. Under mixed-bundling the products are offered as a bundle and are also sold separately.

The marginal cost of supplying the two products is assumed to be independent of the amount produced. The marginal cost of supplying the two products as a bundle is equal to the costs of supplying the two products individually. Fixed costs are not considered in this scenario.

The customers in the market each have a maximum amount of money they are willing to pay for each of the products. Each of these prices is called willingness-to-pay (WTP). In the following chapter willingness-to-pay will be defined more closely. At this point it is only important to know that willingness-to-pay refers to the maximum amount of money a person is willing to pay for some product.

The WTPs for the two products are known individually and the consumers behave as follows:

1. A consumer buys a product only if his or her willingness-to-pay is greater than the price of the product. When a consumer buys a product he or she realizes a surplus, which is the difference between the willingness-to-pay and the sales price.

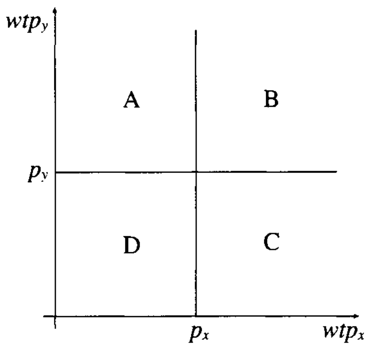
2. In pure bundling the two products are viewed as one product by the consumers and the WTPs for the two products sum up to the willingness-to-pay of the bundle. This implies that there are no dependencies between the two products and the corresponding WTPs.

3. In mixed-bundling consumers have the same valuations for the two products sold separately and for the bundle. A consumer chooses the combination of products that leaves the highest surplus.

Every customer buys at most one unit of each product. With these underlying assumptions the sales volumes in the market can be depicted for all three strategies. The graphical illustrations in figures 2.2 to 2.4 show different size segments of customers who buy one of two products X and Y, or buy both products separately or in a bundle.

In Figure 2.2 customer segments are shown under a pure-unbundling scenario for two products X and Y. The market is divided into four segments labelled from A to D by the sales prices for the two products denoted by p_x and p_y. Segment A consists of the customers who buy only product Y, segment B consists of the customer who buy both products separately, and those who buy product X are in segment C. Segment D contains the customers who buy nothing.

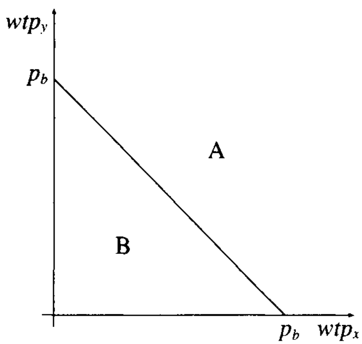
Customer segments under pure-bundling with a price p_b for the bundle are shown in Figure 2.3. The market is divided into two segments, A and B. Segment A consist of the customers who buy the bundle, segment B consists of the customers who do not buy the bundle.



A: Customers buying product Y
B: Customers buying both products
C: Customers buying product X
D: Customers buying nothing

wtp_x: Willingness-to-pay for product X
wtp_y: Willingness-to-pay for product Y
p_x: Price of product X
p_y: Price of product Y

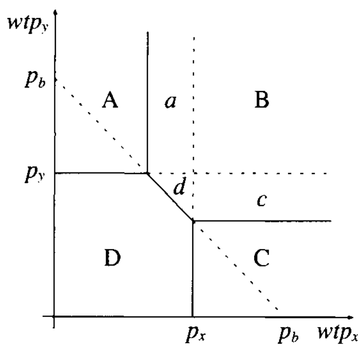
Figure 2.2: Customer segments under pure-unbundling.



A: Customers buying bundle B
B: Customers buying nothing

wtp_x: Willingness-to-pay for product X
wtp_y: Willingness-to-pay for product Y
p_b: Price of the bundle B

Figure 2.3: Customer segments under pure-bundling.



A: Customers buying product Y
B: Customers buying bundle B
C: Customers buying product X
D: Customers buying nothing
a, c, d: Customers switched to bundle B

wtp_x: Willingness-to-pay for product X
wtp_y: Willingness-to-pay for product Y
p_x: Price of product X
p_y: Price of product Y
p_b: Price of bundle B

Figure 2.4: Customer segments under mixed-bundling.

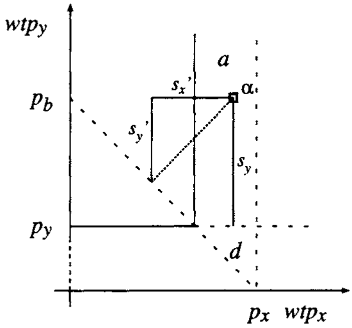


Figure 2.5: Comparison of surplus derived from purchase of bundle and of product Y.

Figure 2.4 shows the customer segments under mixed-bundling. The prices for the two products are the same as under pure-unbundling, and the bundle price is the same as under pure-bundling. By the prices p_x, p_y, and p_b the market is divided into the four segments A, B, C, and D. Note that segment B, which contains the buyers of the bundle, is larger under mixed-bundling than the segment of the customers who buy both products separately under pure-unbundling. Some of the customers who only bought product Y under pure-unbundling have switched to buying the bundle. These customers are denoted by a. Others have switched from buying product X to the bundle, denoted by c. Some customers have even switched from not buying anything to the bundle, denoted by d. Respectively, the segments A, C, and D are smaller than under pure-unbundling.

The reason why customers switch from a single product to the bundle is that they derive a higher surplus from buying the bundle. This can be seen from the foreshortened Figure 2.5. For willingness-to-pay α in area a the surplus from buying product Y is denoted by s_y. The surplus from buying the bundle is the sum of the perceived surplus from acquiring both products denoted by s'_y and s'_x. The surplus from buying bundle B is higher than the surplus from buying only product Y, $s'_y + s'_x > s_y$. For this reason any customer who has a willingness-to-pay in area a would prefer bundle B over product Y. The same holds for product X, which is left out in Figure 2.5.

The customers in area d did not buy anything under pure-unbundling deriving zero surplus. Since they derive a surplus from buying the bundle under mixed-bundling, they also switch to buy the bundle.

The increase in sales is due to the fact that the segments have different sizes under the different bundling strategies, because the customers behave differently.

With the assumption that the WTPs for the two products sum up to a willingness-to-pay for the bundle, customers can be motivated to purchase the bundle, even though they have a willingness-to-pay below the single price for one of the products. The exceeding consumer surplus for the single product, which the customer would buy separately, is transferred to the other product, and the customer switches to buy the bundle. For some

Customers	Mobile Phone	Headset	Bundle (Phone + Headset)
1	90,- €	10,- €	100,- €
2	80,- €	30,- €	110,- €
3	70,- €	40,- €	110,- €
4	40,- €	50,- €	90,- €

Table 2.2: Example of product bundling and WTPs

customers who did not buy anything under pure-unbundling the surplus from the purchase of the discounted product bundle is spread on the two products. For the customers who buy the bundle the heterogeneity of their WTPs is reduced by combining them to a single willingness-to-pay for the combined product.

By a short numerical example the bundling mechanism of two products will be illustrated. Suppose, there are four customers in a mobile phone market with properties similar to those described above. A monopolistic vendor offers one type of telephone and one type of headset for sale. Let the customers have individually known WTPs which are given in Table 2.2.

Let price for the mobile phone be p_m and for the headset p_h. The unit costs for the two devices are denoted by c_m and c_h. In our our example they are both 10,- €. Customer i purchases a product if his or her willingness-to-pay exceeds the price of the product. The willingness-to-pay for customer i and the mobile phone is denoted by WTP_{im} and for the headset by WTP_{ih}.

The maximization problem for the profit function P for the customers 1 to 4 under pure-unbundling can be formulated as follows:

$$\max \quad P = \sum_{i=1}^{n} \alpha_i \cdot (p_m - c_m) + \beta_i \cdot (p_h - c_h)$$

subject to

$$\begin{aligned} \alpha_i \cdot p_m &< WTP_{im} \qquad \forall\, i = 1, \ldots, n \\ \beta_i \cdot p_h &< WTP_{ih} \qquad \forall\, i = 1, \ldots, n \\ p_m,\, p_h &\in \mathbb{R}^+ \\ \alpha_i,\, \beta_i &\in \{0, 1\}\ . \end{aligned}$$

Under pure-unbundling it would be optimal to offer the mobile phone at 79,99 € and the headset at 39,99 €. Customers 1 and 2 would buy a phone. Customers 3 and 4 would buy a headset. The vendor would realize a profit of 199,96 € (P^*) from the sales of the two products, by $P^* = 2 \cdot (79,99 - 10) + 2 \cdot (39,99 - 10)$. If the vendor offered the headset at 29,99 € , customers 2, 3 and 4 would buy one. With the price for the mobile phone unchanged this would lead to a profit of 199,95 €.

Let the price for the bundle consisting of the mobile phone and the headset be p_b. The willingness-to-pay customer i has for the bundle is $WTP_{ib} = WTP_{im} + WTP_{ih}$. The unit costs of the bundle are $c_b = c_m + c_h$.

The maximization problem for the profit function P for the customers 1 to 4 under pure-bundling can be formulated as follows:

$$\max \quad P = \sum_{i=1}^{n} \gamma_i \cdot (p_b - c_b)$$

subject to

$$\begin{aligned} \gamma_i \cdot p_b &< WTP_{ib} \qquad \forall\, i = 1, \ldots, n \\ p_b &\in \mathbb{R}^+ \\ \gamma_i &\in \{0,1\}\,. \end{aligned}$$

Under pure-bundling it would be optimal to offer the bundle at 89,99 €. All customers would buy the bundle. The vendor would realize a maximal profit (P^*) of 279,96 €. In this market it would be more profitable to employ a pure-bundling strategy than a pure-unbundling strategy.

For mixed-bundling the maximization problem for the profit function P for the customers 1 to 4 can be formulated as follows:

$$\max \quad P = \sum_{i=1}^{n} \alpha_i \cdot (p_m - c_m) + \beta_i \cdot (p_h - c_h) + \gamma_i \cdot (p_b - c_b)$$

subject to

$$\begin{aligned} \alpha_i \cdot p_m &< WTP_{im} \qquad \forall\, i = 1, \ldots, n \\ \gamma_i \cdot (WTP_{ib} - p_b) &< \alpha_i \cdot (WTP_{im} - p_m) \qquad \forall\, i = 1, \ldots, n \\ \beta_i \cdot p_h &< WTP_{ih} \qquad \forall\, i = 1, \ldots, n \\ \gamma_i \cdot (WTP_{ib} - p_b) &< \beta_i \cdot (WTP_{ih} - p_h) \qquad \forall\, i = 1, \ldots, n \\ p_b &< p_m + p_h \qquad \forall\, i = 1, \ldots, n \\ \gamma_i \cdot p_b &< WTP_{ib} \qquad \forall\, i = 1, \ldots, n \\ p_m,\ p_h,\ p_b &\in \mathbb{R}^+ \\ \alpha_i,\ \beta_i,\ \gamma_i &\in \{0,1\}\,. \end{aligned}$$

Under mixed-bundling the bundle is offered at a price below the sum of the prices of the bundled products. Otherwise, there is no incentive for any customer to buy the bundle because the components can be bought separately. With a mixed-bundling strategy it would be optimal to offer the mobile phone at 89,99 €, the headset at 49,99 €, and the bundle at 109,99 €. Customer 1 would only buy the phone, customers 2 and 3 would buy the bundle, and customer 4 would only buy the headset. This would lead to a profit of 319,96 € (P^*), by $P^* = 89,99 - 10 + 2 \cdot (109,99 - 10) + 49,99 - 10$. In this market it would be optimal for the vendor to employ a mixed-bundling strategy, because it leads to higher profits than a pure-bundling or a pure-unbundling strategy.

As can be seen from the example, the profitability of the different bundling strategies depends on the structure of the consumers' WTPs and on the cost structure of the products. In order to select the optimal strategy the marketer requires knowledge of the individual WTPs of all consumers in the market and of the cost structure of the products. These are the main findings that Adams and Yellen (1976) draw from their model. As shown in the empirical investigation for bundling in the Nokia online shop, these two are the main criteria to select a bundling strategy.

Building upon the model of Adams and Yellen (1976) other researchers have generalized the findings by assuming populations of consumers with different distributions of willingness-to-pay. Schmalensee (1984) extended the model for the two product case from individually known WTPs to a distribution of WTPs and analyzes the bundling strategies more formally. He aimed at drawing general findings about the relationship between the WTPs for the bundled products and the variable cost structure. For his model he assumes a bivariate normal distribution for the WTPs. He explains his choice as follows:

> The frequency with which normal distributions arise in the social sciences makes the Gaussian family a plausible choice to describe the distribution of tastes in a population of buyers.
>
> (Schmalensee, 1984)

With this assumption Schmalensee (1984) numerically confirmed that the correlation between WTPs for different products influences the benefit of bundling strategies. If WTPs for two products are negatively correlated, that is one is high, the other one is low, or vice versa, bundled sales with optimal prices lead to higher profits. The structure of the variable costs of the products is also very important. An essential prerequisite for a bundling strategy is that the WTPs of the consumers are higher than the variable costs. With these findings Schmalensee provided conditions under which the use of the different strategies yields the highest profits.

Note that other authors, such as Fürderer (1999) and Olderog and Skiera (2000), also assumed that WTPs for product bundles are normally distributed. In the empirical investigation in this thesis this assumption will be challenged.

Similar results as found by Schmalensee (1984) were derived from a simulation performed by Olderog and Skiera (2000). Their main findings were that the relationship between the variable costs and the WTPs is more important than the correlation between the WTPs. They found that bundling of products that have a similar profitability (price - costs) leads to higher profits than bundling products that have different profitability.

Other researchers have provided optimization approaches for larger bundling problems, as for example Hanson and Martin (1990) and Fürderer (1999). Other authors provided qualitative guidelines derived from empirical findings to design bundling strategies. Examples are Eppen et al. (1991) and Simon and Wübker (1999).

2.4 Summary

This chapter focussed on the role of pricing in the marketing mix, demonstrating its importance and presented sample applications from the literature in which pricing strategies were developed alongside with the development of a marketing strategy. Our empirical investigation aims at the optimization of the pricing strategy of the Nokia online shop in Germany for bundled sales, and pricing of products is of ample importance to the operator of the shop.

In more detail product bundling as a pricing strategy was discussed. A special focus was laid on different types of product bundling and the underlying mechanisms were compared. We have argued that a consumer's behavior to different bundling strategies depends on his or her's willingness-to-pay (WTP) for the bundled components. To show this, graphical illustrations were presented, and by a short numerical example it was demonstrated how different bundling strategies yield different profits.

For the research on product bundling the main findings of the corresponding literature were presented. The main findings are that the products' variable costs and the correlation between the consumers' WTPs for the different products play an essential role when a bundling strategy is employed. It is a prerequisite for bundling that the WTPs of the consumers targeted by bundling are higher than the variable costs of the bundled products. Some researchers suggested that bundling is more profitable, when the individual consumer's WTPs for the different products are negatively correlated. When the customers buy the bundle, the heterogeneity of their WTPs is reduced by combining them to one willingness-to-pay for the combined product.

Chapter 3

Willingness-to-Pay (WTP) in Marketing

"Pricing decisions can be complex and difficult, but they are some of the most important marketing decision variables a manager faces" (Monroe and Cox, 2001).

In designing a pricing strategy, the basis is to set the prices for the goods in view of how much the customers are willing to pay for each of the goods. It is important for the marketer to predict how many of the offered products will be bought at different prices. To predict the demand for different products at different prices the marketer needs a profound understanding of the reaction of his or her customers to different pricing schedules.

There are two distinct concepts that determine how much a customer is willing to pay for goods or services. These are the *maximum price* and the *reservation price*. Both will be introduced and discussed in this chapter. In addition to discussing how consumers make choices for or against goods offered at different prices, it will be illustrated how this behavior differs depending on which concept (maximum price or reservation price) the consumer applies internally.

The main argument is that often a marketer cannot distinguish between the two concepts. Therefore, the subsuming term *willingness-to-pay* (WTP) is used by practitioners as well as by researchers.

Also, it will be rationalized in this chapter that it is reasonable not to distinguish between the maximum price and the reservation price if a pricing strategy is designed. The reason is that regardless of the underlying concept the consumer reaction has the same behavior.

3.1 Maximum Price

The first concept introduced is the maximum price. Following Nagle and Holden (2002, chap. 4) we define it as follows:

Definition 1 ***Maximum Price***
The maximum price (p_{max}) of a product is formed by a consumer as the perceived reference price of the reference product plus the differentiation value between the reference product and the product of interest.

Formally the maximum price for a product can be expresses as

$$p_{max} = p_{ref} + p_{diff}.$$

The maximum price is denoted by p_{max}, the reference value is p_{ref}, and p_{diff} is the differentiation value.

The *reference value* for one unit of a product is the cost of the competing product that the customer views as the best alternative. The *differentiation value* is the value of any differences between the product of interest and the reference product.

It will be illustrated how the maximum price works by example: Suppose a hot summer day at the beach.[1] The value of a cool drink is extremely high for most people - perhaps as high as 10,- € for a bottle of cold water. Economists refer to this value as *use value*, or the *utility* gained from a product. If a vendor walked the beach trying to sell water at 10,- € , the people would probably not be willing to pay what the product is really worth to them. They might assume or even know that a competing seller would give them a better deal. A competing seller could be a supermarket which is located just across the street from the beach. Of course a thirsty person had to walk over to the supermarket, but there he or she could probably buy a bottle of water at the price of 2,- €.

In order to set a good price the knowledge of the utility of a product only helps a marketer in rare occasions. Knowing what economists call *exchange value* and what marketers call *economic value to the customer* is more helpful. This value is determined mainly by what alternatives are available for the customer. In the above example people might be willing to pay 4,- € for a bottle of water from a vendor at the beach, rather than walking to a supermarket across the street. Looking closely at the example, by offering the product "at the beach", the vendor is offering a differentiated product compared to the same product at the supermarket. The differentiated product is worth more to the people who are lying on the beach.

Customer behavior based on economic value can be summarized as follows:

> A products 'economic value,' then, is *the price of the customer's best alternative* (called the *reference value*) *plus the value of whatever differentiates the*

[1]Example adapted from Nagle and Holden (2002, p. 74).

> *offering from the alternative* (called the *differentiation value*). Differentiation value may have both positive and negative elements. [...] *Economic Value* is the maximum price that a 'smart shopper,' fully informed about the market and seeking the best value, would pay.
>
> Nagle and Holden (2002, p. 75)

The economic value a person assigns to a product depends heavily on the circumstances under which it is offered (Balderjahn, 2003, p. 389). Suppose it was Sunday and the supermarket across the street from the beach was closed and the next best alternative was driving 10 minutes to the closest gas station to get a bottle of water. Perhaps then a person at the beach would be willing to pay 6,- € for a bottle of water from the walking vendor. It is important to notice, if either the reference value or the differentiation value changes, the maximum price changes as well.

Different purchase situations under which products are offered are an important issue especially in pricing studies. To approximate real choices of different offerings, the respondents must be put in a situation as close as possible to the real purchasing situation. If a pricing study for different products in an online shop is conducted, it has to take place online in a shop-like environment with the same look-and-feel and offered information as the real shop.

In order to develop a pricing strategy based on economic value Nagle and Holden (2002, pp. 76-82) suggest the separate measurement of reference value and differentiation value. Measurement of the reference value is easier. Often a substituting product can be identified or an average value of the alternative offerings can be calculated. Measuring the differentiation value is more challenging. The differentiating factors of the product being evaluated have to be identified. For each of the factors the positive or negative differentiation value has to be estimated. For objective factors this can often be done by analyzing consumer behavior, for example by analyzing costs of repair that occur when an inferior product is used. For subjective factors differentiation values can be estimated by surveying techniques.

3.2 Reservation Price

Different to the maximum price is the concept of the reservation price. This concept can be described as follows:

> Economists call a person's maximum willingness to pay for something that person's **reservation price**. The reservation price is the highest price that a given person will accept and still purchase the good. In other words, a person's reservation price is the price at which he or she is just indifferent between purchasing or not purchasing the good.
>
> Varian (2003, p. 4)

Unlike the maximum price the reservation price does not depend on a reference product. The reservation price for a product is a monetary equivalent of what the product is really worth to the consumer. That is the *utility* of the product. At the reservation price the consumer extracts the same surplus from purchasing and not purchasing the product. For this dissertation the reservation price is defined as follows:

Definition 2 ***Reservation Price***
The reservation price (p_{res}) of some product is the price at which the consumer is indifferent between consuming or not consuming the good (or any other good of the same product class) at all.

Following Srinivasan (1982, p. 82) a product class is defined to be a set of products from which the utility of consumption is additive separable from all other consumption.

To illustrate the reservation price suppose a different example[2]: In a small town there is a small university which has a number of dormitories on campus. The university has more students than rooms in the dormitories. Every student prefers to live on campus, because the campus is located outside of town. For every student there is some maximum amount of money he or she is willing to pay to live on campus. Consider the student who is willing to pay the most, say 100,- € per month. If the rent for the rooms was set at that price, exactly one room would be rented - to the one student who was willing to pay 100,- €. The price this student is willing to pay is the reservation price. At this price the student is essentially indifferent to living on campus or not.

Consider the student with the second highest maximum amount of money the or she is willing to pay. Let that amount be 85,- €. If the rooms were offered at that price, two rooms would be rented - to the two students who are willing to pay at least as much as 85,- €. The student who pays 85,- € pays exactly his or her reservation price. The student with a reservation price of 100,- € pays a price below the reservation price and realizes a consumer surplus.

The consumer surplus is the difference between what the consumer would be willing to pay and what the consumer actually has to pay (Mansfield and Yohe, 2004, p. 93). From this we derive the definition of the consumer surplus as follows:

Definition 3 ***Consumer Surplus***
The consumer surplus realized from purchasing a product is the monetary difference between the products utility, represented by the reservation price, and the sales price.

3.3 Willingness-to-pay

There is a fundamental difference in the two examples. For the person at the beach the reservation price for a bottle of water was 10,- €. But the highest price he or she was willing to pay was only 4,- €. For the student with the highest reservation price of 100,- €

[2]Example adapted from (Varian, 2003, chap. 1)

for a room on campus the highest price he or she was willing to pay was also 100,- €. In the example with the bottle of water at the beach, the person was willing to pay the maximum price. In the example with the rooms on campus, the student was willing to pay the reservation price.

The difference lies in the circumstances under which the products are offered. The circumstances influence how much an individual is willing to pay for a product. For the example with the rooms on campus the student has no alternative to living on campus but to rent the room at the offered price. So, the choice is either to live on campus or not to live on campus. In the example with the bottle of water there are competing vendors selling slightly differentiated products. On the beach competition can be observed, for the room rental on campus there is just one landlord.

How much a person is willing to pay depends on the perceived economic value and on the utility of the good. These two values determine whether the price a person is willing to accept is the reservation price or the maximum price. If a person believes that there is no alternative offering, the highest amount of money he or she is willingness to pay equals the utility of the good and is the reservation price. If a person perceives an alternative offering with an economic value below utility, the highest price he or she would accept equals the economic value of the product and is the maximum price.

When a marketer observes a price at which a consumer switches from purchasing to not purchasing or vice versa, often it cannot be determined whether that was a reservation price or a maximum price. In this case a more general term for this price is applied. Following Dowdeswell (1995, Annex 6, Glossary) this price is defined here as the *willingness-to-pay.*

Definition 4 ***Willingness-to-pay (WTP)***
The willingness-to-pay is the highest price an individual is willing to accept to pay for some good or service.

Based on the circumstances outlined above two purchase situations can be identified:

Purchase situation $p_{max} \leq p_{res}$:	The reservation price is higher than or equal to the maximum price.
Purchase situation $p_{max} > p_{res}$:	The reservation price is below the maximum price.

In purchase situation $p_{max} \leq p_{res}$ the reservation price remains an unobservable variable because willingness-to-pay is determined by the maximum price. Consider the example with the bottle of water at the beach. Although the person had a higher reservation price, the observed willingness-to-pay was only 4,- €.

In purchase situation $p_{max} > p_{res}$ willingness-to-pay is determined by the reservation price. In the example for of the rooms on campus the marketer can observe that all students who did not rent a room at 100,- € had a reservation price below this amount. When the price is lowered step by step and more students rent rooms, the reservation prices of these students can be observed.

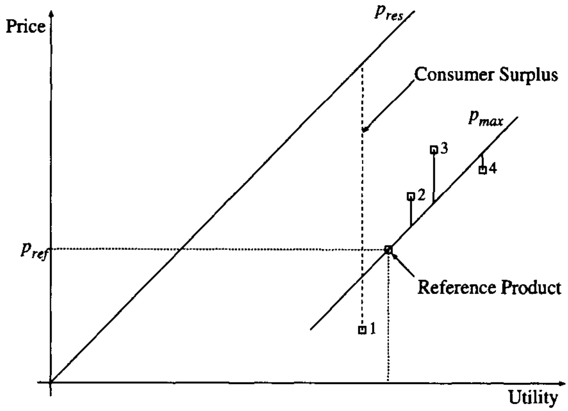


Figure 3.1: Purchase situation $p_{max} \leq p_{res}$ with four products.

Note that in this example the maximum price equals the current rent, as there is no alternative. The reference product is the same room in the dormitory, and the differentiation value is zero. For the student who rented a rom for 100,- €, the purchase situation was $p_{max} = p_{res}$.

For the graphical presentations of the two purchase situations a different example will be used. Think of the market of PDAs (personal digital assistant). The price of a PDA ranges from approximately 100,- € to a couple of hundred. There exist many different brands, and many vendors offer a great variety of competing products. For any type of PDA offered at a selected price there exists an alternative offering, hence, competition always exists. A person who buys a PDA has a reservation price above or equal to the sales price. A person who chooses not to have a PDA simply does not value them high enough to actually purchase one. He or she has a reservation price below the maximum price.

Figure 3.1 shows purchase situation $p_{max} \leq p_{res}$ for one consumer who is facing four different PDAs offered at different prices. The consumer has a very high utility for PDAs and therefore a reservation prices well above the usual market prices. The reservation prices for different products are denoted by the reservation price line p_{res}. The consumer perceives the product offerings 1 to 4 as having different economic values. These economic values are formed from the perceived sales price of the reference product p_{ref} offset by the differentiation values. From the economic values of the products the maximum prices are formed. The maximum prices for the four products lie on the maximum price line, denoted by p_{max}. PDAs 2 and 3 are offered at prices above the consumer's maximum prices. Therefore, the consumer would not buy any of these two. PDAs 1 and 4 are priced below the consumer's maximum prices. Out of these two the consumer chooses one, which offers the highest consumer surplus, that is, the positive differential between

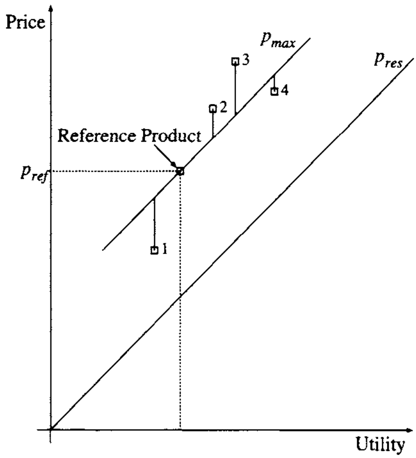


Figure 3.2: Purchase situation $p_{max} > p_{res}$ with four products.

the reservation price and sales price. The consumer chooses product 1.

Figure 3.2 shows purchase situation $p_{max} > p_{res}$ for a different consumer facing four different PDAs. This consumer does not need a PDA. When he or she builds a maximum price, for any product offering this price will be somewhere in the usual price range of PDAs. Since the consumer does not need one, for every product offering he or she has a reservation price below the maximum price. The consumer's reservation prices are denoted by the reservation price line p_{res}, the maximum prices by the maximum price line p_{max}. Since the reservation price line is below the maximum price line, the consumer chooses not to buy any product offering, and it can be seen that the lower price of the two concepts determines the willingness-to-pay.

3.4 Treatment of Willingness-to-Pay in Marketing

Usually a marketer is not interested in whether willingness-to-pay is determined by the reservation price or the maximum price. It is more important to correctly predict consumers' choice behavior when they are presented different products at different prices.

The fact that marketers are not so much interested in the difference between the reservation price and the maximum price can be seen from the following quotes from the current marketing literature. The quotes show that researchers do not distinguish clearly between the two concepts.

> ... each customer has a maximum price they are willing to pay for a given product which equals the product's value to the customer. This price is the

> consumer's reservation price for the product. The consumer compares her reservation price for each product with its purchase price and chooses the product that offers the largest differential.
>
> Kalish and Nelson (1991)

> ... the upper price threshold is referred to as the buyer's *reservation price.* Regardless of the term used, it recognizes that at a specific point in time there is a maximum price that buyers are willing to pay for a product or service.
>
> Monroe and Cox (2001)

> The reservation price is the maximum price a consumer is willing to pay for a certain good. Since the reservation price is the upper limit of the acceptable price range for a product, it corresponds directly with the perceived value of the good. If a consumer purchases a good at a price below the perceived value, he or she realizes a consumer surplus.
>
> Balderjahn (2003, p. 389)

Upon examination of literature there does not appear to be any discussion in the marketing literature on the differentiation between reservation price and maximum price. We will investigate in the next section whether the missing differentiation is reasonable.

3.5 Linearity and Parallelism of Different Concepts

In Figures 3.1 and 3.2 it is assumed there are two important properties for the curves describing the reservation price and the maximum price: Firstly, the curves are linear and secondly they are parallel.

If these two properties are true, a marketer need not know whether willingness-to-pay is determined by reservation price or by maximum price because the only difference is whether the value scale reflects utility or economic value. Both scales can be represented by an interval scale with the same unit length and can therefore be transformed onto one another by addition or subtraction. Both properties of the curves, linearity and parallelism, will be justified in the following.

Starting with linearity of the relationship between utility and price as expressed by the reservation price line, and between economic value and price as expressed by the maximum price line. The intuition of the argumentation is that if a consumer does not buy a product at a certain price, he or she saves the corresponding amount of money for later consumption. We believe that a consumer perceives additional 2,- € for consumption to be twice as beneficial as an additional 1,- €. If this is true, the two relationships must be linear.

Investigating this relationship further exploits a concept that economists refer to as the composite good. In any purchase situation money that is not spent on some good is automatically spent on the composite good. The composite good stands for everything else a consumer might want to consumer other the good of the current purchase situation (Varian, 2003, p. 21).

If a consumer does not buy a product in a certain purchase situation, he or she automatically spends the money on the composite good. For the amount of money which can be spent on the composite good, the consumer will choose a combination that yields the highest possible consumer surplus.

If the same consumer spends the same amount of money on the composite good a second time, he or she will again choose a combination that yields the highest possible consumer surplus. Because the composite good is infinitely large and arbitrarily divisible, the consumer can always find a combination that yields the same highest possible consumer surplus as the first time. Since the same amount of money is spent, the utility values of the two combinations must be the same, in order that the surpluses are the same. Therefore, the relationship between utility and price must be linear.

The assumption of a linear relationship between utility and price was also used by other authors. Jedidi and Zhang (2002) for instance define the composite good to have a linear utility function.

The linearity between economic value and price, that is, the maximum price, will now be examined. It is only necessary to have look at purchase situation $p_{max} \leq p_{res}$, because only then the consumers' purchase behavior is determined by the maximum price. In this situation a consumer does not accept the price for a product if it exceeds the maximum price.

Here it is assumed that the product the consumer is currently faced with belongs to a class of products. In addition to the definition of a product class given in Section 3.2, we define that for each class of products there exists only one reference product, for which the consumer has a perceived market price. This implies that if a consumer perceives different reference products for similar goods, these goods belong to different product classes.

As there is only one reference product in a class the differentiation of all other products is perceived in terms of utility. Therefore, the maximum price of every product is offset to the price of the reference product by a price that reflects the differentiating amount of utility. Because the relationship between utility and price is linear, the relationship between the economic values of the products in the class and price must also be linear.

From this argument it follows directly that the reservation price line and the maximum price line must also be parallel. This is due to the fact that the difference in terms of utility of the products in a class corresponds to the same price difference. This does not depend on whether the prices are offset to the maximum price or the reservation price of the reference product.

In Figure 3.3 a purchase situation $p_{max} \leq p_{res}$ is shown. The curves of the reservation price p_{res} and the maximum price p_{max} are linear and parallel. The line representing the reservation price goes through the natural origin of the utility scale. In terms of utility all products can be compared even if they belong to different product classes. If a product has zero utility, a consumer would not pay any money for acquiring the good.

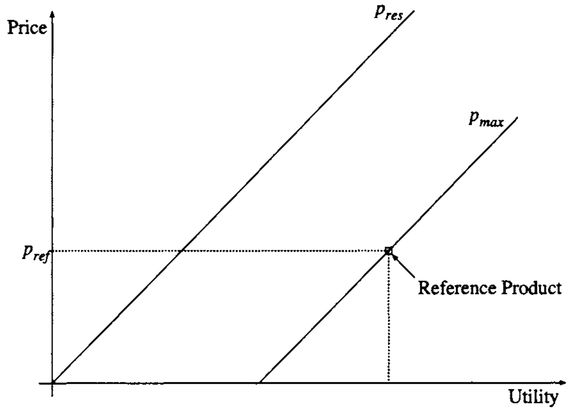


Figure 3.3: Maximum price and reservation price for a product class.

At the intersection of the maximum price line and the utility scale the consumer would not pay any money for a product, even though it has a positive utility value. The intersection represents the zero point of the economic value scale of the product class. Because the differences between the products of the class are measured in terms of utility, it follows that the economic value scale is an additive transformation of the utility scale.

3.6 Excursion: Economic Theory on Reservation Price

By applying standard economic theory it can also be shown that the relationship between utility and price must be linear. The argument depends on the assumption that the composite good has a linear utility function.

Following Varian (2003, p. 63) a utility function for two products X and Γ can be formulated as

$$U(x,\gamma) = u_X(x) + u_\Gamma(\gamma). \tag{3.1}$$

Hereby x is the amount of some product X, for which the reservation price is not known, and γ denotes the amount of the composite product Γ. We assume that the function $U(x,\gamma)$ is quasilinear, that is, can be written as in Equation (3.1) with $u_\Gamma(\gamma)$ contributing linearly to the utility and $u_X(x)$ being any monotone increasing function with $u_X(0) = 0$ and $u_\Gamma(0) = 0$.

$$U(1,\gamma) > U(0,\gamma') \qquad \text{where} \qquad \gamma' > \gamma. \tag{3.2}$$

On the left hand side of this equation the utility is given for an individual who consumes one unit of product X and consumes some amount of the composite good. On the right hand side of the equation the customer does not consume product X and therefore consumes a greater amount of the composite good denoted by γ'. An individual will choose to consume product X if he or she derives a higher utility from consuming the product than from not consuming it.

As shown in Section 3.2 the reservation price for a product X is defined as the price at which the consumer is just indifferent between consuming good X or not consuming it. Therefore, the reservation price p_X^* for one unit of product X is found, when the customer is indifferent between purchasing or not purchasing the product. Formally, indifference can be expressed by the following condition:

$$U(1,\gamma) = U(0,\gamma') \qquad \text{where} \qquad \gamma' > \gamma. \tag{3.3}$$

When consuming the goods X and Γ at the unit prices p_X and p_Γ, each consumer is confronted with an individual budget constraint which can be defined as $m = p_X x + p_\Gamma \gamma$. Since the composite good is defined to be arbitrarily divisible, the price for one unit of Γ can be set to 1 (Varian, 2003, p. 21). For the consumption and non consumption of one unit of product X the following equations derived from the budget constraint hold

$$\gamma = m - p_X \tag{3.4}$$
$$\gamma' = m. \tag{3.5}$$

For the sake of formal simplicity and since only the case of buying one or zero units of X is considered, let u_X denote the utility of consuming one unit of product X, that is $u_X := u_X(1)$. Using the quasilinear utility function in Equation (3.1) the condition for indifference in Equation (3.3) can be rewritten as

$$u_X + u_\Gamma(\gamma) = u_\Gamma(\gamma'). \tag{3.6}$$

Since $u_\Gamma(\gamma)$ is linear with $u_\Gamma(0) = 0$, it can be replaced with a line with slope k and intercept 0 in Equation (3.6) resulting in

$$u_X + k \cdot \gamma = k \cdot \gamma'. \tag{3.7}$$

Applying the budget constraint from Equations (3.4) and (3.5) the following condition for the consumption of one unit of product X at the reservation price p_X^* can be formulated

$$u_X + k \cdot (m - p_X^*) = k \cdot m. \tag{3.8}$$

Applying some simple arithmetic to the equation m can be eliminated. Then, if the utility and the reservation price for one unit of product X is known, the slope k of the utility function of the composite product Γ can be calculated by

Brand	Part-Worth
Mercedes	10
Honda	3

Color	Part-Worth
Green	1
Blue	2

Table 3.1: Example of cardinal utility.

$$k = \frac{u_X}{p_X^*}. \tag{3.9}$$

Economically, the factor k represents the exchange rate between utility and money. With the factor k the reservation price for any product configuration for which the utility is known can be calculated.

3.7 Excursion: Cardinal versus Ordinal Utility

Economists of the nineteenth century treated utility as measurable in a cardinal sense. This changed in the twentieth-century. In modern economics utility is treated as measurable in an ordinal sense (Mansfield and Yohe, 2004, p. 56). The treatment of utility in an ordinal sense provides an ordering according to preference of different product bundles. Any numbers attached to this ordering do not bear any information besides bundles with a higher number being preferred over a bundles with a lower number. A utility function is "simply a way to represent or summarize a preference or ordering. The numerical magnitudes of utility levels have no intrinsic meaning" (Varian, 2003, p. 69). This less restrictive assumption is sufficient to model most scenarios in economics.

However, describing a preference structure in terms of a ranking is not always sufficient in a marketing context. For a marketer it is important to know, how much more some individuals prefer one alternative over another. Though it is difficult for a consumer to state how much more he or she likes some bundle over another (say twice as much), a cardinal scale exists.

A consumer can very well state that he or she likes some product a lot more than another, compared to two other products between which the consumer is almost indifferent. Even though these differences cannot be elicited from consumers directly, they can be estimated by analyzing a sufficient number of preference decisions.

Consider a simple example. Some conjoint analysis procedure estimates utility values for the attributes of a car for one specific consumer. These values form an additive utility function, which represents the preference structure of the consumer.

Suppose only the attributes brand and color are relevant, because the other attributes are held constant. The attribute's levels and estimated part-worths are given in Table 3.1.

Then, four different cars can be constructed from the attributes: A green Mercedes with utility 11, a blue Mercedes with utility 12, a green Honda with utility 4, and a blue Honda with utility 5. These utility scores not only permit a ranking of the cars, blue Mercedes (12) $\succ$ green Mercedes (11) $\succ$ blue Honda (5) $\succ$ green Honda (4), as in ordinal utility theory, but the utility scores also permit the conclusion that having a Mercedes over a Honda, regardless of the color, is a lot better than having a Honda in the preferred color. In other words, with everything else equal only little is gained from having a blue Honda instead of a green Honda $(5 - 4 = 1)$. Much more is gained from having a green Mercedes than having a blue Honda $(11 - 5 = 6)$.

Marketing instruments to estimate preference structure from consumers treat utility at least in a cardinal sense. In conjoint analysis, for example, every product is assumed to consist of a certain number of attributes. These attributes are assigned numerical values representing cardinal utility. In pricing studies these cardinal utility values are assigned relative of even absolute prices. With absolute prices, such as estimations of willingness-to-pay, the utility scores are used as ratio scales.

3.8 Summary

In this chapter the concepts maximum price (p_{max}) and reservation price (p_{res}) were introduced and discussed. For a consumer there exist two types of purchase situations, $p_{max} \leq p_{res}$ and $p_{max} > p_{res}$. In both situations the amount of money a consumer is willing to pay for a good is determined by the lower concept. That is, in the former the consumer is willing to pay p_{max} in the latter the consumer is willing to pay p_{res}.

From examples of the current marketing literature we have demonstrated that researchers usually do not distinguish between the two concepts. If one does not distinguish between the two, the term willingness-to-pay can be used. Under this term both concepts subsume.

We have proposed a justification that willingness-to-pay can be used when the marketer is only interested in the consumers' purchase behavior when they are confronted with different prices. The justification depends on the argument that the reservation price and the maximum price have a linear relationship with the products utility. Furthermore, the reservation price line and the maximum price line are parallel. Hence, consumer choice based on maximum price and on reservation price have the same behavior, and the only difference is an additive transformation. Therefore willingness-to-pay is a sufficient concept and can be applied when consumer purchase behavior is analyzed.

Chapter 4

Measuring Willingness-to-Pay

In many companies pricing decisions are made without profound understanding of the likely response of the buyers and competitors. These companies do not conduct pricing research and as a result do not have a serious pricing strategy in a marketing sense. They rather have something that could be called an intuitive pricing strategy. Several studies indicate that only 8% to 15% of the companies conduct serious pricing research to develop effective pricing strategies (Monroe and Cox, 2001). Other studies have shown that 49.9% of the surveyed companies adjust prices once or less in a typical year. Further, only 13% of the prices that were changed were a result of a scheduled review of the current pricing policy (Monroe, 2003, p. 19).

In contrast to what seems to be common practice, managers consider the knowledge of customers' response behavior to different prices to be the cornerstone of most marketing strategies, particularly in the areas of product development, value audits, and competitive strategy (Anderson et al., 1993).

On the importance of valid estimates of willingness-to-pay (WTP) researchers agree with managers. Balderjahn (2003, p. 387) considers valid estimates of willingness-to-pay to be essential for developing an optimal pricing strategy in marketing. Such estimates can be used to forecast market response to price changes and for modeling demand functions.

In this chapter different methods that are applied for measuring willingness-to-pay are introduced. We classify these methods and give references to substantial theoretical and empirical work. The advantages and drawbacks of the methods are discussed. The discussion of the different methods clearly indicates that *the best* method that should be used does not exist. Rather it depends on the objective of the marketer. If costly methods can be applied and quick results are not of main interest, different pricing strategies can be tested with field experiments in real market settings. If estimations of willingness-to-pay are needed frequently, it can be more efficient to apply less time consuming and less costly surveying techniques.

At the end of the chapter it will be demonstrated that within indirect surveying there is a method missing which has both the ability to estimate willingness-to-pay at the individual level based on each respondents information and explicitly elicits choice behavior during the interview.

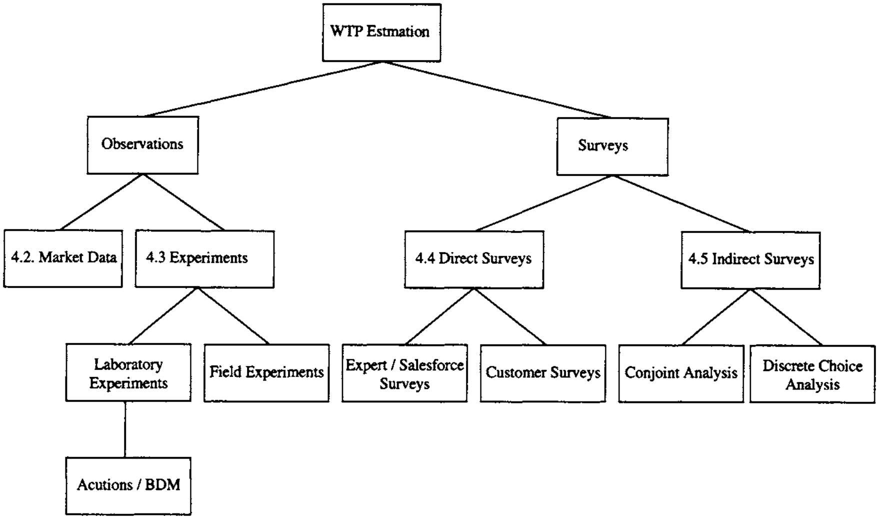


Figure 4.1: Classification of methods for estimation of willingness-to-pay.

4.1 Classification of Methods

A classification of methods to estimate willingness-to-pay is presented in Figure 4.1. On the highest level the methods can be distinguished whether they are surveys or based on data from observations. Taking a closer look at observations, real data can be used, such as market data, or experiments can be performed. Experiments can further be divided in field experiments and laboratory experiments. Within field experiments one can further distinguish, whether the probands are aware they are participating in an experiment or not. Observations are also referred to as *revealed preference.*

Looking at surveys for estimation of willingness-to-pay there exist direct surveys and indirect surveys. Preference data derived from surveys is also referred to as *stated preference.* In direct surveys probands are asked to state how much they would be willing to pay for some product. In indirect surveys some sort of rating or ranking procedure for different products is applied. Conjoint analysis is an indirect surveying method.

A different classification can be found in Marbeau (1987). The author distinguishes the measurement methods on the highest level, whether they are monadic tests or competitive tests. In the former price information is elicited without considering a competitive context. In the latter a competitive context is present.

Balderjahn (2003) distinguishes estimation methods on the highest level, whether they elicit price information at the individual level or at aggregate level.

Nagle and Holden (2002) classify techniques for measuring price sensitivity at the highest level into uncontrolled and experimentally controlled measurement of the variables. Further they classify the techniques based on the variable measurement, dividing into measurement of purchase behavior and measurement of purchase intention.

All classifications are capable in order to describe methods for estimations of willingness-to-pay. However, the structure of this chapter is based on the classification presented in Figure 4.1.

4.2 Analysis of Market Data

Often market data is used to estimate demand curves. As shown in Figure 4.1, market data are classified as observations. Usually it contains sales data.

There exist three kinds of sales data suitable for estimation of willingness-to-pay: (1) *historical sales data* - the companies' own sales records, (2) *panel data* - individual purchase data from members of a customer panel, and (3) *store scanner data* - sales records from individual sales outlets. Using historical data is based on the assumption that past demands can be used to predict future market behavior. This implies that the product for which future demand is estimated has only been exposed to minor variations in the product profile. This also applies to competitors and consumers. A problem is that often historical data does not contain the necessary price variations to cover the desired spectrum of WTPs. If the price variations are too small, response to variations outside of the market data can only be hypothesized. The necessary price variation often appears to be a pitfall when analyzing historical sales data. Sattler and Nitschke (2003) classify estimation of willingness-to-pay based upon market data as not feasible, since only very few datasets contain the necessary variations. Demand curves based upon sales data is usually modeled with regression techniques. But this is only possible if the requirements of the independent variables are met (cf. Balderjahn (2003, p. 399) and Nessim and Dodge (1995, p. 72)).

Note that historical sales data is often available only at the aggregate level. The data is aggregated over time and different stores are combined. Single customers are usually not identified, which makes individual level estimations impossible. This is different with panel data. The actual prices paid for products are observed at the individual level. The drawbacks are that having a customer panel is very costly to companies. Furthermore, it is often questionable, whether the customer panel adequately represents the market as a whole (Nagle and Holden, 2002, p. 335).

Scanner data is usually aggregated at store level. It is usually not aggregated over time. Therefore it is useful for observing response to short time price variations. Because of the store level aggregation, individual level repeated purchase behavior cannot be extracted from scanner data.

Using market data the researcher can only observe whether an individual or a group had a willingness-to-pay above the product price, because the product was actually purchased. Customers who refused to purchase the product are not reported in historical sales data.

4.3 Experiments

Generally experiments can be distinguished between laboratory experiments and field experiments. Both types can be applied in pricing studies. In laboratory experiments purchase behavior is typically simulated by giving the probands an amount of money and asking them to spend the money on a specific selection of goods. The goods and prices are varied systematically. Methods for accessing price response of this form have been by applied by Silk and Urban (1978) in their well-know ASSESSOR procedure. In laboratory experiments the results are obtained quickly. A drawback is that the probands are aware of the experimental situation. This might lead to subjects becoming more rational of their purchase behavior compared to their normal shopping behavior which can lead to low external validity (Nessim and Dodge, 1995, p.74). Another source of bias might be the artificial setup as described above, in which the proband either does not take real possession of the goods purchased, or does not use his or her own money (Nagle and Holden, 2002, p. 341).

Field experiments or in-store purchase experiments do not suffer from the problem of the artificial setup because they are performed in the natural environment of the consumers. Depending on the experimental setup the proband knows that he or she is participating in an experiment. Field experiments are often carried out in form of test markets. In different test markets the prices are systematically varied and the consumers' responses are analyzed. A crucial issue is to select test markets as similar to the target market as possible.

The drawback of field or in-store experiments lies primarily in the relatively high costs (Nagle and Holden, 2002, p. 341). Generally, both types of experiments are costly compared to surveying techniques. Sattler and Nitschke (2003) also identify the high costs performing test markets and other field experiments as the main disadvantage of this type of estimation techniques.

4.3.1 Vickrey Auction

A special case of laboratory experiments are auctions. Auctions have been intensively tested to elicit willingness-to-pay.

If a seller knew the true valuations of the customers, there would be no need for an auction. The seller would simply sell the good to the bidder with the highest valuation at a price close or equal to that valuation. If the seller is uncertain about customers valuations, an auction is a valuable instrument to sell the item at a good price. Therefore, an auction is useful to gain knowledge of consumers' valuations of a good and can therefore be used to reveal consumers' valuations of goods to facilitate future pricing decisions.

According to Wertenbroch and Skiera incentives to reveal true willingness-to-pay can be provided with Vickrey auctions (Vickrey, 1961). "Vickrey suggests that incentive compatibility is ensured if a given bid determines only whether the bidder has the right to buy the good that is auctioned off" (Wertenbroch and Skiera, 2002). The auction takes place in sealed form, and the purchase price is determined by the second highest bid. A participant in a Vickrey auction submits a bid containing how much he or she would be willing to pay in sealed form, for example in a closed envelope. If the participant has the highest bid, he or she wins the auction. However, the participant only has to pay the price of the second highest bid. Therefore, if n participants bid in a Vickrey auction the n'th highest bid wins the auction at the price of the $n-1$'th highest bid. With this mechanism the participants are provided an incentive to reveal their true bid, because they must buy the good if their bid wins the auction (Vickrey, 1961).

Consider a Vickrey auction with two participants Anton and Beatrix. The item for sale is worth 100 € to Anton and 99 € to Beatrix. Assume that Beatrix bids her exact willingness-to-pay of 99 €. If Anton also bids his true willingness-to-pay of 100 € , he wins the auction and only pays the amount of Beatrix's bid of 99 €. He realizes a positive surplus of 1 €. If Anton bids below his true valuation, for example 95 €, he will not win the auction. Furthermore, Beatrix wins and pays a price that Anton also would have accepted. Now consider a third bidder Christian who has a valuation of 101 € and bids this valuation. If Anton bids above his true valuation, for example 105 € , he wins the auction and has to pay 101 € for the item. He has to pay more than his true valuation and therefore realizes a negative surplus. The example shows that it is always optimal for Anton to bid his true valuation in a Vickrey auction. The same holds for Beatrix and Christian.

Skiera and Revenstorff (1999) tested the ability of Vickrey auctions to reveal consumers' WTPs. The authors test a sample of slightly more than 50 MBA students at the University of Kiel in the year 1996. Different mobile-phone contracts were offered in a Vickrey auction. The contracts had different conditions, and the bids were placed for the monthly base fee. The mechanism of the auction was described to the students, and the optimal bidding strategy was explained (which is bidding the true valuation).

As is common in preference measurement the authors used holdouts to test the estimated preferences. Holdouts are used to test if the estimated preference structure can be used to correctly predict preference or choice for a number different products. These products for which the preference structure is tested are called holdouts. In Skiera and Revenstorff's experiment the probands were asked to rank different mobile-phone contracts given a base fee. Only probands were considered, who had at least on bid above one of the holdout stimuli. With this the probands who would not accept any of the offered contracts were rejected from the experiment. Out of the remaining probands, a fraction of roughly 20%, the most preferred choice could be predicted based on the bids. Whether the estimated WTPs correspond to real purchase behavior, was not tested in this study.

Based on an additional questionnaire the probands seemed to have a good understanding of the mechanism of the auction. The optimal bidding strategy was less clear to the probands. The bids of the probands are positively correlated to information about monetary income and probability of renewing a contract in the near future. Therefore, the bids seem to be reasonable.

In a different experimental setting Sattler and Nitschke (2003) compared different methods to estimate willingness-to-pay. In their experiment they tested for external validity by requiring the respondents to purchase an item at a willingness-to-pay estimated by one of the different methods. One of the tested instruments was the Vickrey auction another was a first-price auction. In a first-price auction the bidder with the highest bid wins and purchases the item at the price of his or her own bid. Sattler and Nitschke (2003) find that the Vickrey auctions in addition to the first-price auctions both tend to overestimate consumers willingness-to-pay. The authors suppose that this effect is due to the overbidding phenomenon. The overbidding phenomenon occurs when bidders strategically place bids above their true willingness-to-pay to increase their chance of winning (Kagel et al., 1987).

Based upon the empirical evidence presented in the literature the use of Vickrey auctions cannot clearly be suggest nor discouraged for the estimation of willingness-to-pay.

4.3.2 Becker, DeGroot and Marshak Procedure

If one accepts that experimental auctions, such as the Vickrey auction, can be used to estimate willingness-to-pay, there is a vast field of research of how to design such auctions. Another method that is incentive compatible, in the sense that the best strategy for the bidders is to bid their true willingness-to-pay, is the well-known BDM procedure named after Becker, DeGroot and Marshak (Becker et al., 1964). In BDM every participant simultaneously submits an offer price to purchase a product. Then, a sale price is randomly drawn from a distribution of prices. The possible prices cover an interval from zero to a price greater than the anticipated maximum price, which any bidder would submit. The bidders whose bids are greater than the sale price receive a unit of the good and pay an amount equal to the sale price. The mechanism is incentive compatible for the same reason as the Vickrey auction: A given bid determines only whether the bidder has the right to buy the good that is auctioned off. The price is set by some mechanism and is below the participants bid.

BDM was tested by a number of researchers for its ability to forecast willingness-to-pay. Wertenbroch and Skiera (2002) tested it in a field experiment. The authors find BDM a feasible, reliable, and valid market research procedure. The participants of the experiment easily understood the BDM method and hardly any of the approached individuals refused to participate. Data was easily gathered in several hundred interviews. Reliability was determined by comparing mean WTPs across four daily respondent sub-samples. Validity was determined by relating the estimated WTPs to data from an additional questionnaire asking the respondents to rate their desire of the tested products.

In a laboratory experiment Wertenbroch and Skiera (2002) tested BDM in combination with a purchase obligation. After the experiment the participants rated how satisfied they were with their purchase. The buyers as well as the non-buyers were extremely satisfied with the outcome of the BDM experiment. This result indicates that BDM does not suffer from the overbidding bias, which is found in some Vickrey auctions.

In a recently published study Noussair et al. (2004) compare the Vickrey auction with the BDM mechanism. The authors test the two mechanisms with respect to firstly a bias of bids to the true valuation of the objects being auctioned, and secondly which mechanism leads to bids closer to the true valuation, and thirdly which mechanism converges towards the true valuations more rapidly. In their experimental setup the optimal bidding strategy (bidding the true valuation) is not explained to the probands. The aim of their study is to measure the probands ability to find that strategy under the two mechanisms.

A large experiment was carried out in France with almost 200 probands chosen by drawing names randomly from a local telephone directory. The probands bid for different consumer goods. Each proband was assigned a true valuation drawn randomly from a predefined distribution of valuations. Without going into the details of the experimental setup, the authors find that under the Vickrey auction the bias from the true valuation is more rapidly reduced. That is, the probands learn the best bidding strategy more quickly. Another measure, the dispersion of bids, is also narrowed more rapidly under the Vickrey auction than under the BDM mechanism. The authors argue that the reason for this difference lies in the fact that a deviation from the optimal strategy is more costly under the Vickrey auction than under the BDM mechanism. Therefore, the probands learn the bidding strategy quicker under the Vickrey auction. Another reason is that the Vickrey auction seems to be easier to understand than the BDM mechanism. With respect to these results the authors report "our research indicates that, given the procedures we have used in our study, the Vickrey auction is preferable to the BDM mechanism as an instrument for the elicitation of the willingness-to-pay for private goods" (Noussair et al., 2004).

The applied research of experimental auctions to estimate willingness-to-pay is rather limited. Still, the underlying auction mechanisms make this approach an appealing research area for estimation of willingness-to-pay.

4.4 Direct Surveys

According to the classification direct surveys can be distinguished between expert judgments and customer surveys.

4.4.1 Expert judgements

Expert judgements is one of the most frequently used methods for estimating customers willingness-to-pay in order to estimate demand at different price levels. They can be performed more quickly and at lower costs compared to interviewing customers.

For expert judgments usually sales or marketing people predict the willingness-to-pay of their customers. Since sales representatives work directly in the market and in close connection with the consumer, they are aware of the structure of competition and are sensitive to trends in consumer needs. Therefore, interviewing sales people is an important source of information for demand estimates. Nevertheless, the opinion of sales people might be biased because of colliding objectives between the marketer and the sales force. Usually the sales force's rewarding system is tied to sales volume. This can result in intentionally or unintentionally overstated or understated estimates (Nessim and Dodge, 1995, p. 70).

Letting marketing experts estimate product demand under different price schedules might suffer from the distance to the market and the consumers. In contrast to estimates provided by sales people there are no incentives to over- or understate true estimates. However, an opinion of a single expert is always a subjective point of view. Usually there are less marketing people in a company than sales people. Resting upon opinions of few marketing people might also lead to erroneous forecasts of future demand.

This type of survey is best applicable to environments with a small number of customers. In such environments the customers are known well enough to correctly predict WTPs. With larger and heterogeneous customer bases this becomes a critical issue.

Despite the shortcomings of expert judgments described above, they are an important source of information because an educated guess is better than a random selection of a presumably adequate price from a number of price possibilities (Nessim and Dodge, 1995, p. 70).

Other authors, for example Balderjahn (2003, p. 391), label expert judgments as a poor marketing instrument with low validity and discourage from its use.

4.4.2 Customer Surveys

Naturally, if one attempts to forecast consumer behavior in response to different prices, a good way is to ask the customers.

One of the oldest methods for estimation of willingness-to-pay is the direct survey. One of the first applications was the *psychological price* method developed by Stoetzel (1954). Stoetzel's idea was that there is a maximum and minimum price for a product. These studies consisted only of two questions as formulated by Marbeau (1987):

1. *Above* which price would you definitely not buy the product, because you can't afford it or because you did't think it was worth the money?

2. *Below* which price would you say you would not buy the product because you would start to suspect the quality?

Directly asking the respondents to indicate acceptable prices is referred to as the *direct approach.* Other researchers have build upon this method and research in this area became quite popular (e.g., Abrams (1964), Gabor et al. (1970), and Stout (1969)).

Van Westendorp (1976) introduced the NSS price sensitivity meter, consisting of four questions. Two additional questions to the questions developed by Stoetzel ask for a reasonable cheap price and a reasonable expensive price. Applications of NSS can be still found in commercial applications.[1]

Several recent methods for direct customer surveying have established themselves. An example is the commercial tool BASES Price Advisor from ACNielsen.[2] This procedure

[1]E.g., the Czech company GFL offers NSS to determine critical price ranges for new or re-launched products, http://www.gfk.cz/en/offer/solution/pricing.aspx, visited June 25th, 2004.

[2]For details see the online resource under http://www.bases.com, visited June 17th, 2004.

presents the probands with several typical product profiles. These product profiles can be in an early conceptual phase or already marketable. The probands are then asked to name prices at which they consider a product to have *a very good value*, *an average value*, and *a somewhat poor value*. From the responses buying probabilities for different prices are derived. According to Balderjahn (2003, p. 392) "a somewhat poor" value could be interpreted as a reservation price.

Instead of directly asking the maximum price for a product, the respondent can be shown a product profile with an assigned price. The respondent then indicates whether he or she would actually buy the product at that price. This is sometimes referred to as an *indirect approach* to customer surveying (Marbeau, 1987). Indirect approaches are discussed in the next section.

Directly surveying customers has some flaws:

1. By directly eliciting willingness-to-pay from customers, there is an unnatural focus on price.

2. Customers do not necessarily have an incentive to reveal their true willingness-to-pay. They might overstate prices because of prestige effects or understate prices because of consumer collaboration effects. Nessim and Dodge (1995, p. 72) suppose that "buyers in direct responding may also attempt to quote artificially lower prices, since many of them perceive their role as conscientious buyers as that of helping to keep prices down". Nagle and Holden (2002, p. 344) observe the opposite behavior. To not appear stingy to the researcher respondents could also overstate their willingness-to-pay.

3. Even if customers reveal their true valuations of a good, this valuation does not necessarily translate intro real purchasing behavior (Nessim and Dodge, 1995, p. 72).

4. Directly asking for WTPs especially for complex and unfamiliar goods is a cognitively challenging task for respondents (Brown et al., 1996). While it remains unclear whether this leads to over- or understating of true valuations a bias is likely to occur.[3]

5. The perceived valuation of a product is not necessarily stable. Buyers often misjudge the price of a product, especially if it is not a high frequency purchase or an indispensable good (Marbeau, 1987). On a shopping trip an individual might have a too high or too low expectation of the price for a product. Directly asked, the individual would state a willingness-to-pay that matches this expected price. When the individual finds out the usual market price for the product during the shopping trip and still decides to purchase, he or she has adapted the willingness-to-pay accordingly.

[3]This effect will also occur in Vickrey auctions, cf. Section 4.3.1. In this type of auctions the participants also have to name a price they are willing to pay for a product. If this product is unfamiliar or complex, this is a difficult task.

A large empirical comparison between a field experiment, a laboratory experiment, and a personal interview was carried out by Stout (1969). In the experiment the prices for different products were varied and the changes in demand were measured. The results showed significant quantity changes on systematic price changes in the field experiment. As expected, the demand for the products decreased as the prices were raised and vice versa. For the other two methods no significant changes in demand for the products could be measured and raised and lowered prices. The personal interview even contained reversals. For some respondents the demand increased when the prices were raised.

Directly asking customers their WTPs for different product seems not to be a reliable method. Balderjahn (2003, p. 402) explicitly alludes to the distortional effects of direct surveys and advise against its use. (Nagle and Holden, 2002, p. 345) states that "the results of such studies are at best useless and are potentially highly misleading".

4.5 Indirect Surveys

In contrast to directly asking respondents for their WTPs, they can be presented product profiles with a price assigned and be asked to indicate whether they would purchase the good at that price. In an approach proposed by Camron and James (1987), the authors suggest to present to a random sample of probands random product profiles with assigned prices. "Across the selection of product scenarios, the investigator is free to vary not only the proposed price, but also the levels of all other product attributes. Each consumer's willingness or unwillingness to purchase the specific product at the designated price is recorded. If the experimental design includes variability in the levels of prices, product attributes, and consumer characteristics, the researcher will be able to us the statistical techniques [...] to calibrate the demand function" (Camron and James, 1987).

Since the respondent is presented a number of products with assigned prices, a real purchase situation is mimicked more closely than in direct surveys in which the respondent has to state an acceptable price. Furthermore, it is cognitively easier for a respondent to decide whether a specific price for a product is acceptable, than to directly assign a price (Brown et al., 1996). When the respondent is presented competing product alternatives, he or she can be asked to select his most preferred choice or apply a preference ordering. Applications of this type are presented in the next two sections.

4.5.1 Conjoint Analysis

Conjoint analysis is a technique designed to elicit individuals' preference structures for types of products. When this technique is used, different product alternatives, systematically varying the attributes of the product, are presented to the respondent. A product's attribute is a set of possible realizations. These realizations are referred to as the attribute's levels. An example of one of many attributes of a car is its color. The levels could be red, white, black, and so forth. The respondent is presented a number of product profiles consisting of realizations of the product's attributes and brings them in a rank order. This rank order is used to estimate the relative contribution of the different attribute levels to the overall valuation.

Conjoint analysis has been used for measuring willingness-to-pay by many authors, (e.g., Hanson and Martin (1990), Eppen et al. (1991), and Venkatesh and Mahajan (1993)). Usually price is included in the conjoint analysis and treated as an attribute or feature of the product. As for the other attributes the contribution of price to the overall valuation is computed for different levels of price. When a participant has completed a conjoint analysis, it can be predicted which product out of a number of available products with assigned prices is most attractive.

From the preference information it cannot be estimated whether the respondent would also buy the product at the assigned price. Therefore, researchers usually assume some kind of status quo product at a price the respondent would actually accept. This product is used as an anchor against which all other products are priced. For example, the marketer assumes some product configuration with a price as the status quo product, and then adjusts the price of some other product such that it becomes equally attractive as the status quo product. This approach relies heavily on the assumption that the respondents would accept the status quo product at the given price. If the consumers were not willing to pay the price for the status quo product in the first place, they would also not be willing to pay the estimated prices for other product configurations.

One attractive approach to estimate willingness-to-pay by conjoint analysis was proposed by Voeth and Hahn (1998). This method does not rely on a status quo product. Instead, the probands bring the product profiles in a rank order and then insert a so-called Limit-card. Up to the position of the Limit-card the respondent would be willing to purchase the product profile at the indicated price, below the Limit-card the respondent would not purchase the product. The authors label their approach Limit-conjoint-analysis. Voeth and Hahn understand the position of the Limit-card as the origin (the absolute zero) of utility. They then transform the estimated contributions of the product features onto a ratio scale. Based upon this scale a price for each product profile can be found such that each has a utility of zero to the respondent. These prices are the respondent's WTPs for the products.

A similar approach was used in an empirical study by Sattler and Nitschke (2003), who let the probands order different product profiles with prices and ask them to indicate those which they would actually purchase. The stimulus with the lowest overall part-worth is used as anchor point to calculate all other WTPs.

Unlike regular conjoint analysis in which the researcher selects a status quo product, the respondent selects the status quo product, which is the position of the Limit-card. With this the main source of error, selecting an inappropriate status quo product, is avoided.

One drawback still arises from the configuration of prices by the researcher. In a conjoint interview the attribute price is usually configured to cover the range of usual market prices. This is problematic for respondents who have a willingness-to-pay way above or below the average market price. These respondents rate or rank a large number of profiles with prices assigned that are far displaced from their willingness-to-pay. It can happen that the relevant product stimuli are only presented in very few conjoint questions and therefore few relevant data-points are elicited.

4.5.2 Discrete Choice Analysis

In discrete choice analysis the respondents choose between alternative products (McFadden (1980), McFadden (1986)). Discrete choice analysis is also referred to as *choice-based* conjoint analysis (Louviere and Woodworth, 1983). The connection to conjoint analysis lies in the ability of both methods to decompose products into attribute levels and estimate part-worth utilities for these levels. Methodologically the two methods are quite different. Whereas conjoint analysis estimates the part-worths for each respondent individually based on the respondents' data only, estimates with discrete choice analysis are obtained only at the aggregate level using the data of all respondents. For discrete choice analysis a latent utility structure for the population that is surveyed is estimated instead of the utility structure for each member of the population individually.

The utility structure is estimated based on a choice set available to all probands. Every choice can be fully described in terms of its attributes. The probands are presented different choices at the same time and indicate which one they would actually choose. Often the respondents are provided a no-choice alternative, to indicate that they would not choose any of the presented product profiles.

A latent preference for every choice in the evoked set is assumed to exist at the aggregate level. The evoked set refers to the set of possible products or brands the respondent is currently considering in the decision process. This latent preference is estimated based on choices between different product profiles the probands make during the analysis. For every proband the utility value for a choice is modeled consisting of a deterministic component, that represents the latent preference structure at the aggregate level, and a random component. The random component is due to fluctuations in perceptions, attitudes, or other unmeasured factors (McFadden, 1986). Depending on whether the random component is normally or logarithmically distributed, the model is referred to as a probit-model or a logit-model. The more common model is the logit model.

Based upon random utility theory, the utility that an individual i assigns to some alternative can be described as

$$U_i = V_i + \epsilon_i.$$

In this notation U_i is the unobservable, but true utility of alternative i. V_i is the observable or systematic component of utility and ϵ_i is the random component.

Price is included as an attribute of the product profile and the levels cover the range of the possible and meaningful prices. The probability for the choice for a specific alternative i from a specific choice set can be described by the multinomial logit model

$$P_C(i) = EXP(V_i) \; / \; \sum_{j \in C} EXP(V_j).$$

"In this model, $C = \{1, 2, ..., M\}$ denotes a set of available alternatives, indexed from 1 to M, and P is the probability that an individual when presented with this set will choose alternative i" (McFadden, 1986). Note that V does not depend on the individual. This parameter describes the latent preference structure of the population. The unknown parameters V_j for all alternatives $j \in C$ are typically estimated from the data by a maximum likelihood procedure. The probability for a product P_C is used as a market-forecast and can be viewed as the potential market share.

Since part-worths for different prices are estimated, a change in price can be expressed in terms of change in utility. The exchange rate between utility and price can be calculated. Given this exchange rate the willingness-to-pay for any product profile relative to the most preferred choice in an individual's evoked set can be calculated. An example of an empirical study using this approach can be reviewed in Balderjahn (1991).

As can be seen from the estimation procedure described above, discrete choice modeling aims at estimating preference structure at the aggregate level. In this approach it is not possible to directly estimate part-worths at the individual level because usually too few data points are elicited. This is due to the fact that the observation of a choice out of an evoked set only contains information about the chosen product and not about the remaining products. This is different in conjoint analysis in which a ranking or rating of all products is provided by the respondent. Therefore, the preference structure for an individual can be estimated based upon the data elicited in the corresponding conjoint interview. An individual's preference structure cannot be estimated from the data elicited in a single discrete choice interview.

In many applications, for example in order to forecast the market share of a new product, aggregate level estimation of preference is sufficient. However, in many situations it is desirable to obtain estimates of every individual's preference structure. From data elicited by discrete choice analysis part-worth estimations at the individual level can be obtained in a postprocessing task utilizing a hierarchical Bayes approach. This approach will be described in the next section.

4.5.3 Hierarchical Bayes

From data collected by a discrete choice task part-worths at the individual level cannot directly be estimated because the dataset is too sparse. In such cases Hierarchical Bayes (HB) Methods can be used to recover individual preference heterogeneity even with insufficient degrees of freedom (Lenk et al., 1996). Especially HB can be used to estimate individual part-worths for choice data (Allenby and Ginter, 1995). To obtain individual level estimations a "Monte Carlo Markov Chain" method (MCMC) can be used which utilizes a "Bayesian" approach to estimate the part-worths.

In a HB approach the part-worths of the individual probands are assumed to be drawn from a multivariate normal distribution. With this assumption the probability of one specific realization of the part-worths drawn from one specific multivariate normal distribution given a dataset can be expressed by utilizing Bayes's rule as

$$p(H_j \mid y) = \frac{p(y \mid H_j) \cdot p(H_j)}{p(y)}.$$

In this notation H_j describes one hypothesis of a sequence of hypothesis, $j = 1, 2 \ldots$. Each hypothesis contains the parameters of the multivariate normal distribution from which the part-worths of the individuals are drawn. The probability of one specific realizations of the part-worths for each individual from the distribution of the hypothesis is $p(H_j)$. The dataset is represented by the symbol y. Since the data set is the same for all hypotheses, it can be regarded as a constant. With $p(y)$ being constant for all H_j's the equation can be rewritten as the proportional relationship

$$p(H_j \mid y) \propto p(y \mid H_j) \cdot p(H_j).$$

It can be seen that the posterior probability that a hypothesis given the data is true has a proportional relationship to the likelihood of seeing the data given the hypothesis times the prior probability of the hypothesis.

The parameters of each subsequent hypothesis are formed only based upon the current parameters of the multivariate normal distribution. The parameters are selected such that the fit of the model to the dataset is improved in each step. Repeating this process many times makes this an MCMC approach.

The Hierarchical Bayes approach is called "hierarchical" because it consists of two levels. At the upper level the vector of part-worths for each individual i is drawn from a multivariate normal distribution described by

$$b_i \sim N(\alpha, C)$$

in which α is a vector which contains the means and C a matrix which contains the variances and covariances of the part-worths of the population.

At the lower level a logit model is assumed for each individual describing the probability of choosing the selected products in the choice tasks in the dataset. See the previous section for details of the multinomial logit model.

The procedure starts with initial estimates for b_i for all individuals and estimates for α and C. To simplify the notation the estimates of the part-worths for all individuals are denoted by the vector b in the following. With the parameters α, C, and b the following steps are repeated for a large number of times:

1. Estimate a new realization of part-worths b_{new} which fits the dataset better than the previous one taking the current α and C into account. This estimation is done with a "Metropolis-Hastings" algorithm which contains the "Bayesian" nature of the process.

2. With the new vector b_{new} and the dataset C a new vector α_{new} is estimated.

3. With the new vector b_{new} and the new vector α_{new} a new matrix C_{new} is estimated.

The subsequent estimations of α_{new} and C_{new} can be done with straight-forward statistical techniques (cf. Sawtooth Software Inc. (2003)).

In the "Metropolis-Hastings" algorithm the vector b_{new} is produced by adding a small random perturbation to each element of the current vector b. The likelihood of the data given b_{new} is estimated with the logit model. The prior probability that b_{new} is drawn from the multivariate normal distribution $N(\alpha, C)$ is estimated. According to Bayes' theorem, the posterior probability that the parameters α and C of the model and the realization b_{new} given the data is true is proportional to the likelihood of seeing the data given the parameters of the model times the probability that the realization b_{new} is drawn from the model. The new vector is accepted if the posterior probability is greater than the current posterior probability with the current vector b. Otherwise, b_{new} is accepted with a probability equal to the ratio between the new and the current posterior probability.

By repeating the procedure a large number of times the estimations for the parameters α, C, and b converge. Once a desired convergence rate is reached, the process is continued for a large number of iterations. From these iterations the average values for the elements of the b's are used for the final estimation of b.

By considering the multivariate normal distribution describing the part-worths of all respondents the procedure "offers a very powerful way for 'borrowing' information from every respondent in the dataset to improve the accuracy and stability of each individual's part worths" (Orme, 2003, p. 5). The borrowing of information is achieved by estimating the underlying multivariate normal distribution that describes the part-worths of the respondents.

Several empirical investigations have shown that individual level part-worths estimated with HB have a comparable internal validity as estimations based on conjoint analysis when the same amount of information is given for the estimation procedures. The benefit of HB estimation is that it can be used with sparse data to produce individual level estimations with high internal validity (cf. Lenk et al. (1996) and Sawtooth Software Inc. (2003)).

4.6 Empirical Evidence

An early comparisons between direct surveys eliciting willingness-to-pay, conjoint analysis using ranking, and conjoint analysis using rating was performed by Kalish and Nelson (1991). The experiment was conducted among undergraduate and first year graduate students of different business classes. The authors tested the three approaches in terms of their predictive validity on holdout products. The products of the experiment were airline tickets described on the non-price attributes service level, seating room, and non-stop. In the direct survey the respondents were asked to name their willingness-to-pay for different product configurations. Willingness-to-pay was explained to the students as the amount of money that would make them indifferent between purchasing the ticket and keeping the money. For the two conjoint approaches prices covering the usual range of typical prices in the market were assigned to the product configurations. For the ranking the students were asked to bring the products into a preference order, for the rating the students were asked to distribute a number of rating points over the presented products. The main goal of Kalish and Nelson's experiment was to test for internal validity by predicting holdout products. At the end of every survey the participants were presented four product profiles (so-called holdouts) with assigned prices and were asked to indicate their preferred choice. The predicted choices derived from the data of the three surveys were compared to the actual choices of the respondents. The predictive validity of the conjoint models based on rankings as well as the model based on ratings clearly outperform the model fit from the directly elicited WTPs. 62% of the first choices were correctly predicted in the two conjoint approaches compared to only 46% for the direct survey. The authors find that directly surveying willingness-to-pay "is not as robust to respondent involvement as are ranks or ratings" (Kalish and Nelson, 1991).

More recently researchers tested different approaches to estimate willingness-to-pay for external validity. Sattler and Nitschke (2003) performed an empirical comparison of the methods direct enquiry, conjoint analysis, first-price auction, and Vickrey auction. The authors elicited willingness-to-pay for different prepaid telephone cards among students. Each of the students was exposed to all four instruments in random order. Based upon the estimates of willingness-to-pay derived from the four instruments Sattler and Nitschke systematically tested for differences. Furthermore, they tested for external validity by requiring a sub-sample of each instrument to purchase a telephone card at the indicated willingness-to-pay. One of the elicitation methods was randomly selected for each student, and the student was required to buy a telephone card. All approaches except the two auction mechanisms differ pairwise significantly in estimations for WTPs. The results of the study indicate that willingness-to-pay is systematically higher in hypothetical settings where the probands do not have to make a purchase at the end. In real settings, with a purchase at the end, the estimated WTPs are systematically lower. These findings are consistent with other studies, for example Harrison and Rutström (2004) and Wertenbroch and Skiera (2002). Sattler and Nitschke find this bias for the methods conjoint analysis, ascending auction, and Vickrey auction. The authors could not observe it in the direct enquiry. Note that in the real setting with a purchase at the end the estimated WTPs also differ significantly pairwise between the four methods. Therefore, the authors cannot draw a conclusion which method mimics real market best and should be advised for use.

In a different study Backhaus and Brzoska (2004) used a Vickrey auction to test external validity of WTPs estimated by a conjoint procedure and by discrete choice analysis. The authors assume that the Vickrey auction is feasible to elicit true product valuations and therefore can be used to test hypothetical procedures for external validity. For the conjoint procedure a Limit-card was used as described above. The object of their study is a selection of four different DVD players for which the probands could place bids in a Vickrey auction after completing one of the two interviews. Backhaus and Brzoska constructed a price response curve for each player from the observed bidding data. Price response curves were also constructed based upon the data elicited by conjoint analysis and by discrete choice analysis. The authors then compared the curves of the WTPs. The comparison showed that the two hypothetical procedures substantially overestimated the willingness-to-pay for the participants of the experiment. At the aggregate level the overestimation of the conjoint approach was smaller than the overestimation of discrete choice analysis. However, at the individual level underestimations of WTPs also occurred which lessens the overestimation at the aggregate level. Based upon their empirical findings Sattler and Nitschke (2003) advise against the use of conjoint analysis with price as an attribute and discrete choice analysis to estimate willingness-to-pay.

4.7 Summary

In this chapter different methods to estimate consumers' WTPs for different products have been discussed. The methods were classified into four classes: Analysis of market data, experiments, direct surveys, and indirect surveys. All methods have different advantages and drawbacks.

Market data represent real purchase behavior. Therefore, willingness-to-pay derived from the real demand is very reliable and has a high external validity. However, in many marketing situations market data cannot be used. For products that are not yet released in the market, for example new or differentiated products, there exists no market data. Also, often the prices in the market do not contain the necessary price variations. Without such price variations demand at different price levels cannot be estimated.

Using experiments the problem of missing products or price variations can be overcome. In this approach willingness-to-pay for different products is also estimated by observing purchase behavior. In an experiment the products and prices can easily be adapted such that the participants are presented the necessary variations. Depending on the artificial setup the participants are more or less aware they are participating in an experiment. However, experiments are time-consuming and costly. Therefore they are not suitable in many management situations.

Less time-consuming and costly are surveys. In surveys the respondents only state their choice or desire for a number of products. Real purchase behavior is not observed. Within surveys a distinction is made between direct surveys and indirects surveys. When willingness-to-pay is estimated with a direct survey, the respondent is directly asked to state how much he or she is willing to pay. This approach has a number of possible biases. Often it is difficult to state a willingness-to-pay for an unfamiliar product. Also, respondents sometimes overstate their willingness-to-pay because of prestige effects, or understate their willingness-to-pay because of customer collaborations effects (help to keep the prices down).

Within surveys an indirect approach is the preferred method for the estimation of willingness-to-pay. In indirect approaches the respondents are presented a number of different products with assigned prices and have to choose the most preferred one or have to apply a ranking to the products. Based upon the choices the respondents make, or the rank order they apply, WTPs for the different products can be estimated by statistical techniques.

We have discussed two types of indirect surveys: Conjoint analysis and discrete choice analysis (also referred to as choice based conjoint). Both can be used by marketers to estimate willingness-to-pay. Conjoint analysis estimates the WTPs for the respondents at the individual level based on every respondent's data. In discrete choice analysis shares of WTPs are estimated at sample level. For this the data provided by the whole sample of respondents is used.

Estimation of willingness-to-pay at the individual level is important if the market for which price response is to be estimated is heterogeneous. For heterogeneous samples or samples for which the degree of heterogeneity is not known, individual level estimation is better suited.

However, it is possible to estimate individual level WTPs from choice data. For this task a Hierarchical Bayes approach can be used. The estimations for every individual are performed by using information provided by the whole sample of the respondents. It is not possible to estimate willingness-to-pay for each respondent based on the individual's choice data only.

In conjoint analysis individual level willingness-to-pay is estimated based on each respondent's data only. But other than discrete choice analysis the classical conjoint analysis approach does not have a decision process included in the interview. That is, the respondent is never asked whether he or she would actually buy a product. The respondent only applies a preference order for the presented products. With respect to the presentation technique to the respondent this is regarded as the main disadvantage of conjoint analysis compared to discrete choice analysis. Letting the respondent choose rather than rate or rank mimics real purchase behavior more closely.

To estimate product choice at different prices based on conjoint data marketers usually assume a status quo product. The respondents of the interview are a priori believed to buy this product. The willingness-to-pay for a competing product is then estimated as the price at which the respondent would switch away from the status quo product. With this approach WTPs cannot be estimated for customers who would not buy the status quo product in the first place or have a different status quo product. To avoid this respondents can be allowed to select a status quo product themselves.

An overview of the discussed characteristics of the four methods to estimate willingness-to-pay is presented in Table 4.1. By definition, the difference between the first two methods and the surveying techniques is that in the latter the respondents do not purchase anything. Table 4.1 shows that within indirect surveying there is a method missing that combines the advantages of the two presented techniques. The advantages and drawbacks of conjoint analysis and discrete choice analysis are the ability of the former to perform estimations of willingness-to-pay at the individual level based on each individual's provided information and of the latter to elicit choice behavior during the interview.

In view of this we have developed a new estimation procedure that firstly performs all estimations at the individual level and secondly elicits choice behavior during the interview. This surveying technique will be presented in Chapter 7. The new procedure works as an extension of conjoint analysis. In order to discuss how this extension is integrated

	(1) Market data	(2) Experiments	(3) Direct surveys	**(4) Direct surveys**	
				Conjoint analysis	Discrete choice analysis
Real purchase behavior	Yes	Sometimes	No (by definition)	No (by definition)	No (by definition)
Flexible product & price variations	No	Yes	Yes	Yes	Yes
Time-efficient & cheap	No	No	Yes	Yes	Yes
Observed choice behavior	Yes	Yes	No	**No**	**Yes**
Individual level estimations based on each respondent's data	No	No	Yes	**Yes**	**No**

Table 4.1: Characteristics of different estimation techniques for willingness-to-pay.

into conjoint analysis we will discuss conjoint analysis first. An introduction covering the relevant parts of conjoint analysis is presented in Chapter 5.

Chapter 5

Conjoint Analysis

In the previous chapter the ongoing research in the estimation of willingness-to-pay (WTP) was reviewed, providing an overview of the different methods and discussing advantages and disadvantages. Also, reviewed were the different methods in respect of their ability to estimate consumers' preferences at the individual level.

In Chapter 7 a new procedure to estimate consumers' willingness-to-pay for different products will be presented. This procedure works as an additional interview scene in combination with conjoint analysis, and we named it PE scene. This new approach uses previously elicited preference structure at the individual level as input.

Because the PE scene is an extension of conjoint analysis an introduction to conjoint analysis is given in this chapter. The intention of this chapter is not to give the reader a comprehensive overview of conjoint techniques. The interested reader is referred to Gustafsson et al. (2000). Instead the reader is given an idea of how different conjoint techniques work. The goal is to show how conjoint analysis can be combined with the PE scene. In view of this different techniques are discussed especially focusing on adaptive conjoint analysis (ACA), because in our empirical investigation the PE scene was combined with ACA.

5.1 Introduction

Conjoint Analysis is a decompositional method in which the probands are presented a selection of stimuli consisting of different attributes or components and state their preferences. These attributes have different levels. From these preferences utilities of the levels of the attributes are derived. The utilities can then be used to predict future preferences. MarketVision Research describes this process as follows:

> ...conjoint methods, though, share the basic tenet of decomposing products into their component parts to *analyze* how decisions are made and then *predict* how decisions will be made in the future. That is, conjoint analysis is used to understand the importance of different product components or product

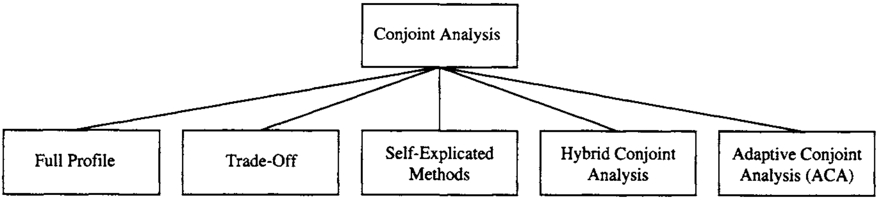


Figure 5.1: Classification of conjoint methods based on data gathering techniques.

> features, as well as to determine how decisions are likely to be influenced by the inclusion, exclusion, or degree of that feature.
>
> (MarketVision Research, 2002, p. 1)

The first paper in a scientific journal on the applicability of conjoint analysis to consumer behavior was published by Green and Rao (1971). In the following years many papers were published on the topic discussing different algorithms and applications. Conjoint analysis quickly became widely used and is today an integral part of market analysis in marketing as can be reviewed in various papers about applications of conjoint analysis (e.g., Wittink and Cattin (1989), Wittink and Burhenne (1994), Voeth (1999), Hartmann and Sattler (2002a), and Hartmann and Sattler (2002b)).

Green and Srinivasan (1990) define conjoint analysis to be "any decompositional method that estimates the *structure* of a consumer's preference (i.e., estimates preference parameters such as part-worths, importance weights, ideal points), given his or her overall evaluations of a set of alternatives that are prespecified in terms of levels of different attributes". As Green and Srinivasan here we will narrow this definition to methods that estimate the preference structure of the respondents at the individual level. This is done, because individual level preference data is utilized in the PE scene.

Conjoint methods can be distinguished in terms of their data gathering and presentation techniques. A taxonomy of different conjoint methods based on this is presented in Figure 5.1. In this taxonomy the methods are restricted to pure conjoint methods. Other authors, for example Carroll and Green (1995), suggest a broader taxonomy for conjoint methods regarding all methods that have the ability to estimate part-worths.

Throughout this dissertation we do not consider discrete choice analysis to be a conjoint method. The main similarity between discrete choices and conjoint analysis lies in the presentation technique to the probands and that decompositional part-worths are being estimated. Because of this similarity discrete analysis is also referred to as choice-based conjoint (CBC). Nevertheless, the underlying preference model and the parameter estimation techniques are different. Furthermore, the approach estimates part-worths only at the aggregate level, in contrast to the main advantage of conjoint analysis which is part-worth estimation at the individual level (Balderjahn, 2003, pp. 400-401). Therefore, we will not discuss discrete choice analysis in the context of conjoint analysis. For an overview of discrete choice analysis see Section 4.5.2.

Prior to starting this discussion of different conjoint methods an introduction of some key terms will be given. In conjoint analysis products are considered to be decomposable into their features. These features are called *attributes*. The realizations of such an attribute are called *levels*. Consider a mobile phone: The features of such a telephone include display and ring-tone. In a conjoint study regarding mobile phones the features display and ring-tone would be considered as attributes. The realizations of these attributes could be color display versus monochrome display or different display sizes. The realizations of ring-tones could be the number of melodies or simple and polyphonic ring-tones. These realizations are the levels of the attributes.

In a conjoint study *part-worths* are estimated for all attribute levels. That is each level is assigned a number, such that the respondents' preference structure based on the attributes and levels is represented. Part-worths are also referred to as part-worth utilities or utilities and will be used synonymously. The measurement focusing on the different attributes is called *importance*. The importance of one attribute is based on the level's part-worths and simply describes the range of the part-worths from the least preferred to the most preferred level.

The conjoint methods considered here have the underlying assumption, "that the utility of a product is the sum of the values attaching to its separate attribute levels" (Johnson, 2001). This assumption is referred to as an additive compensatory model (Young, 1973). In this model the utility of a product is calculated as the sum of the part-worths of the levels of all attributes. The model is called compensatory because it is assumed that high and low part-worths of attribute levels compensate one another. Consider the mobile phone again: Some individual might prefer a color display over a monochrome display. Additionally, the individual attaches much more value to having polyphonic ring-tones than to the type of display. Then, he or she might prefer a telephone with a monochrome display and polyphonic ring-tones over a telephone with a color display and simple ring-tones. In this case the gain from polyphonic ring-tones has compensated the loss from having a monochrome display.

The rank order for telephones for this individual could be:

1. Polyphonic ring-tones and color display
2. Polyphonic ring-tones and monochrome display
3. Simple ring-tones and color display
4. Simple ring-tones and monochrome display

The rank order of the products is formed based upon the part-worths. The utility of each product is calculated as the sum of the part-worths. The calculated values for all possible products represent the preference structure of the respondent.

Telephone 1
monochrome simple

Telephone 2
monochrome polyphonic

Telephone 3
color simple

Telephone 4
color polyphonic

Figure 5.2: Full profile conjoint cards for telephones with the attributes display and ring-tone.

5.2 Full Profile

The classic conjoint method is full profile conjoint analysis (Green and Rao, 1971). In full profile conjoint analysis the probands are presented product profiles that are described as a combination of the levels of all attributes. These full profile stimuli are presented on cards with textual and/or graphical descriptions of the products. Reusing the example with the mobile phones, suppose a study regarding the features ring-tone and display. In the design of the conjoint analysis the attribute ring-tone could have the levels simple and polyphonic. The attribute display could have the levels color and monochrome. With two attributes both having two levels each $2^2 = 4$ stimuli cards can be constructed. A possible textual presentation of the cards is given in Figure 5.2.

Typically, the respondents would bring the product cards in a preference order. This approach is called full profile ranking. The presentation of a product described in terms of attributes and levels is also referred to as a product stimulus.

Using the additive compensatory model the utility structure of a respondent for the product stimuli based upon the attributes a and the corresponding levels l, can be described as follows:

$$y_c = \sum_{a=1}^{A} \sum_{l=1}^{L_a} \beta_{al} \cdot x_{al}$$

with

$$\begin{array}{lcl} y_c & : & \text{Rank of product card c} \\ \beta_{al} & : & \text{Unknown part-worth of level } l \text{ of attribute } a \\ x_{al} & = & \begin{cases} 1 & \text{if product card } c \text{ has level } l \text{ of attribute } a \\ 0 & \text{otherwise.} \end{cases} \end{array}$$

From the rankings of the product cards the parameters β_{al} of the respondent's preference structure can be fitted. If the rankings of the respondent are treated using an ordinal scale, typically MONANOVA (Kruskal, 1965) is applied. If the rankings are assumed to be equidistant, they can be treated using an interval scale. Then OLS regression or ANOVA can be applied. Various studies have shown that different estimation procedures do not lead to significantly different results (e.g., Cattin and Wittink (1976), Carmone et al. (1978), and Wittink and Cattin (1981)).

Usually a conjoint study is much larger than in the example given above. In order to fit the part-worths of the attribute levels a sufficient number of stimuli cards containing the levels must be presented to the respondent. Once the part-worths are fitted, a utility score for any stimulus composed from the attributes and levels can be predicted using the same additive composition rule. Note that a score can also be calculated for product stimuli that were not actually presented to the respondent during the study.

If the number of product cards is large, the probands are sometimes asked to pile the cards in several piles ranging from "very attractive" to "not attractive at all" in order to reduce cognitive overhead. The piles are then ranked separately. As the number of attributes and levels increases, the number of stimuli combinations increases exponentially. A study with two attributes with 3 levels each has $3^2 = 9$ stimuli combinations. A product described on five attributes consisting of three levels each leads to $3^5 = 243$ stimuli combinations.

A design plan presenting the respondent with all possible stimuli is called a *full factorial design*. Sometimes interaction effects between attribute levels occur. Certain combinations of attribute levels might lead to a higher or lower valuation of the product stimulus than when they do not occur together. For example, if a certain combination of attribute levels does not make sense, this would lead to a lower overall valuation and affects the parameter fitting. If interactions between attribute levels do not occur, only main effects are studied. Most conjoint studies estimate main effects, and interaction effects are assumed to not exists (Green and Srinivasan, 1990).

In conjoint studies estimating main effects the respondents need not rank all possible stimuli. When the number of stimuli is reduced, this is called a *fractional factorial design*. A reduced selection of stimuli should represent the full number of stimuli as close as possible. This is usually done using an orthogonal design (Addelmann, 1962). In an orthogonal design the proportional frequency of occurrence of any attribute level in the full design is maintained in the reduced design. That is, for any combination of two attributes the levels of one attribute must occur with equal frequency with the levels of the other attribute. A discussion of various kinds of fractional factorials can be found in Green et al. (1978).

Apart from ranking in full profile conjoint ratings can be used. Instead of ranking the alternatives the respondents rate them on a (say) 1-7 attractiveness scale (Huber, 1997) or a (say) 0-100 purchase likelihood scale (Mahajan et al., 1982). The estimation of the part-worths works analog to the estimation procedure for ranking data as described above.

5.3 Trade-Off Method

In contrast to the full profile method the trade-off method confronts the respondent with only two attributes at a time (Johnson, 1974). This is done for all attribute pairs. The pairs are presented to the respondent in so-called trade-off tables or trade-off matrices, which list all possible combinations of attribute levels. The intention of using trade-offs instead of full profiles is to reduce the information overload that occurs on part of the respondent when all possible attributes are present in a product stimulus (Green and Srinivasan, 1978).

Using the mobile phone example, assume a third attribute color (for the telephone) with

		Ring-Tone	
		Simple	Polyphonic
Display	Monochrome	...	...
	Color	...	...

(a) Trade-off table with attributes ring-tone and display

		Ring-Tone	
		Simple	Polyphonic
Color	Black	...	...
	White	...	...
	Silver	...	...

(b) Trade-off table with attributes ring-tone and color

		Display	
		Monochrome	Color
Color	Black	...	...
	White	...	...
	Silver	...	...

(c) Trade-off table with attributes display and color

Figure 5.3: Example Trade-Off cards.

the levels black, white, and silver. A possible realization of the trade-off tables for a conjoint study on the attributes display, ring-tone, and color is presented in Figure 5.3. For all trade-off tables the respondent has to rank the level combinations by distributing numbers ranging from 1 (least preferred) to 4 (most preferred) for the Table 5.3(a), and 1 to 6 for Tables 5.3(b) and 5.3(c).

In view of the presentation technique, the drawback with trade-off matrices is that by decomposing the factors into two-at-a-time partial profiles, there is a sacrifice of realism to the respondent (Green and Srinivasan, 1978). In this sense full-profiles are more realistic. The trade-off method is rarely used in practice (Wittink and Cattin, 1989).

5.4 Self-Explicated Methods

A multi-attribute utility function can be constructed from a compositional model or from a decompositional model. The distinction comes from the underlying estimation procedure.

Decompositional models are derived from decision or rating observations of product profiles. Based upon these observations a parameter estimation technique is applied. These estimates of the parameters are the part-worths. The utility function is then constructed as the sum of the estimated part-worths. Full profile and trade-offs are decompositional methods. The respondent is presented different product profiles and ranks or rates the attractiveness. These observations are then decomposed into part-worths for the different levels.

In contrast self-explicated methods are compositional, because the respondent is asked to rate the different levels directly. A typical compositional procedure entails the following steps (cf. Fischbein (1967) and Green and Krieger (1996)):

1. The decision maker rates the desirability of each of a set of possible levels of each of a set of attributes on (say) a 0-10 scale.

2. Following this, the decision maker rates the importance of each attribute on (say) a 0-10 scale. In this model, a *part-worth* is defined as the product of importance times the associated level's desirability.

The utility function is constructed as the sum of the explicated part-worths. An estimation procedure, where respondents explicitly state attitudes towards attributes and levels is called a self-explicated task.

In the strict definition of conjoint analysis limited to decompositional methods, self-explicated approaches do not belong to the family of conjoint methods (Green and Srinivasan, 1978). Nevertheless they are mentioned here, because they are used in combination with decompositional methods in hybrid models and adaptive conjoint analysis.

5.5 Hybrid Models

Hybrid conjoint analysis contains compositional and decompositional elements. They "combine the ease of administration of self-explicated data with the greater realism afforded by decompositional models" (Green and Krieger, 1996). They have been designed for simplification on behalf of the respondent, especially when the number of attributes and levels is large. Hybrid models were originally introduced by Green et al. (1981).

In hybrid models every respondent is first presented a self-explicated task on all attributes and levels as described in the previous section. With the data obtained preliminary part-worths are calculated for each respondent.

After this every respondent is presented a limited number of full-profile stimuli for evaluation. The number of profiles is reduced in order to reduce information overload. The profiles are chosen and presented to all respondents in such a way that each profile is at least rated by one. The evaluations are pooled and group level part-worth estimates are calculated by dummy variable regression (Green et al., 1981).

The part-worths at the individual level are then fitted with data from the group level estimates of the full profile task by multiple regression analysis. Several empirical studies have shown that cross-validity of hybrid models is better than self-explicated models alone. However, full-profile models appear to be superior of hybrid models (Green and Krieger, 1996).

In newer hybrid models part-worths from a self-explicated task are fitted with individual level estimates from full-profile conjoint. If the number of full profiles is reasonable and an orthogonal design can be applied, individual level part-worth estimates can be calculated for all attributes and levels. This can increase the internal validity measured on holdout scores of hybrid models (Green and Krieger, 1996).

5.6 Adaptive Conjoint Analysis

Adaptive conjoint analysis (ACA) was developed in the beginning of the 1980's when the technological possibility arose to perform computer-administered interviews (Johnson, 1987). In many marketing studies great numbers of product configurations had to be examined which made static paper and pencil conjoint studies with orthogonal designs time consuming and costly. The design of ACA provides a more efficient conjoint method when the number of attributes is large.

Utilizing information from a self-explicated task Johnson (2001) developed an adaptive approach to presenting partial profiles to respondents. Similar to the trade-off method the partial profiles consisted of no more than two attributes. The respondent is presented two partial profiles next to each other and is asked to indicate his or her preference. The task of comparing two partial profiles at a time is a trade-off task and is know as paired comparison.

If the within order of attribute levels is known along with the importance of the attributes relative to each other, in some cases the ranking or selection of one partial profile over another is implicitly given. If one partial profile dominates another on all attribute levels, a ranking or selection need not be asked from the respondent. Omitting these questions the number of questions being asked can be reduced. This procedure allows studies with larger number of attributes and levels as in other conjoint approaches.

The stimuli for paired comparison in ACA are chosen to reduce the uncertainty in the part-worths being estimated. That is, the questions are the most difficult for the respondent to answer and therefore bear the most new information. The attribute levels being used in these questions are the ones that have been used the least in the preceding interview in order to approximate an orthogonal design. After each question the part-worths are updated, and with the new information the next question is selected by the same procedure. Because the questions during the interview are constructed based on the respondents prior answers, this form of conjoint analysis is called adaptive.

ACA was introduced as a microcomputer package by Johnson (1987) and has been discussed by many authors (e.g., Green et al. (1991) and Johnson (1991)). The package was novel in that it combined a computer-based interactive surveying technique with customized stimulus presentations to the respondents. The original ACA software package is distributed by Sawtooth Software Inc.[1] The software used in the empirical study in this dissertation is a modular re-implementation called jAC (Java Adaptive Conjoint)

[1] http://www.sawtooth.com

programmed in Java^{TM} developed by Schmidt-Thieme (2004).

ACA consists of four phases (Johnson, 1987). Each phase will be discussed in the following.

An example of a conjoint study is accessories for mobile telephones. One accessory could be a headset. The levels for headset are the different types. Other attributes are a data cable to connect the telephone to a personal computer, an extra battery charger, and car accessories to connect the telephone to the car stereo. Since the study is about additional accessories, each attribute has a non-level. Screenshots of jAC are used to illustrate the example.

Phase I: Each respondent brings the levels of the attributes in hierarchical order according to his or her preferences.

For the attribute headset in the example different headset models which are levels of the attribute *headset* are ordered by the respondent. This is illustrated in Figure 5.4. The attribute headset consists of the levels "HS-3", "HS-10", and "no-headset". The respondent only needs to order the first two levels, because the level "no-headset" implicitly has the lowest preference.

Sometimes the levels of an attribute have a natural ordering and are therefore not ordered by the respondents. This is the case for binary attributes which are either present or absent. If the attribute data cable of the example only consists of two levels "with" and "without", the rank order is implicitly given. The rank order would be set to "with data cable" followed by "without data cable".

Phase II: The respondent is presented the best and the worst level of each attribute as obtained from phase I. The respondent then indicates the importance of the different attributes on a 1 to 4 rating scale with equal intervals.

A screenshot of the example is given in Figure 5.5. In a combined presentation of the four attributes the respondent indicates the importance on a 1 to 4 scale by clicking one of the four buttons for each attribute. The attributes are referred to by their names. Not shown in Figure 5.5 but in the supplementing text it is pointed out to the respondent that the inclusion of the most preferred level is to be rated against the absence of the attribute. By definition the absence of the level is the least preferred attribute level.

Note that the first two phases of ACA are a self-explicated task.

Phase III: Each respondent is presented a set of paired partial profiles. The two profiles are shown side by side on the screen. The respondent indicates on a nine point equal-interval scale his or her preference for one of the options.

Figure 5.6 shows a screenshot of phase III of jAC. The two partial profiles are described textually and graphically. The respondent indicates which profile he or she prefers and to what extent. This is done by positioning the slider below those profiles at the desired value. Internally the indicated values are rounded and transformed onto a -4 to 4 nine-point scale.

Phase IV: Each respondent is presented a number of full profile concepts, so-called *calibrating concepts*, for which he or she has to indicate a purchase probability from 0% to 100% on a so-called purchase-likelihood scale. These profile presentations are used to calibrate the utilities obtained in the preceding phases. Furthermore, if the analysis does

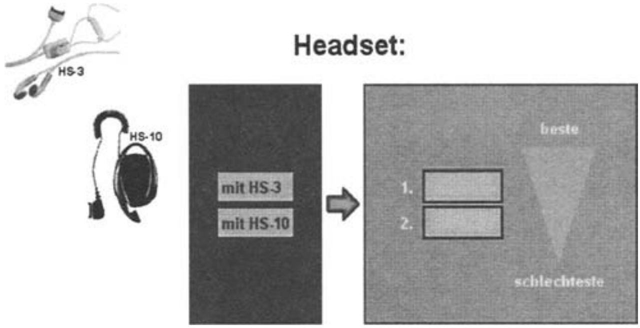


Figure 5.4: Screenshot jAC Phase I.

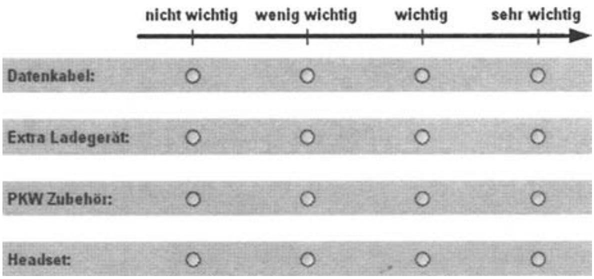


Figure 5.5: Screenshot jAC Phase II.

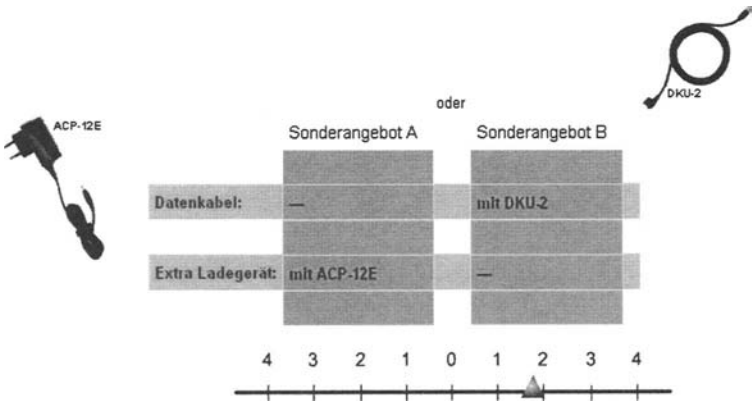


Figure 5.6: Screenshot jAC Phase III.

not include price, the calibrating concepts are used to normalize the estimated part-worths between the respondents onto a comparable scale.

The ranking information from phase I as presented in Figure 5.4 is processed such that the resulting values are centered around zero and scaled to unity. Consider the attribute headset with the levels "HS-3", "HS-10", and "no-headset". With three levels and the preference order assigned by the respondent the procedure works as follows: The levels are first set to the values of the reversed order. That is, the most preferred level has the value 3, the second the value 2, and the least the value 1. Then, the average level value is subtracted. The resulting values for the levels are 1.0, 0.0, -1.0. Finally, the values are scaled to unity. The level's values would then be transformed to 0.5, 0.0, -0.5 (Sawtooth Software Inc., 2002). This procedure has the characteristic that the same intervals are assumed between the attributes levels. Green et al. (1991) point out that this might not describe the preference valuation of the respondents properly and suggest the use of different scales in the self explicated task allowing different intervals at a finer granularity.

The importance stated in phase II is used to scale the ranges of level values of the attributes relative to one another. The importance ratings elicited as shown in Figure 5.5 have values from 1.0 to 4.0. These values are simply used as multipliers for the attribute levels. If the respondent indicates an importance of 3 for an attribute with three levels with the values 0.5, 0.0, -0.5, these values are transformed to 1.5, 0.0, -1.5 (Sawtooth Software Inc., 2002).

The values for the attribute levels are used as initial estimates of the attribute level's utilities for phase III. With each answer the respondent provides the estimates are updated. The updating procedure is modeled as a multiple linear regression model.

$$Xb_n \sim Y$$

In this model X is a matrix of predictor variables with a column for each of the independent variables. Each attribute level is modeled as one independent variable. Each of the n rows is one observation, which is a stimulus presented to the respondent for evaluation. In the vector Y the first n responses are coded. As in standard multiple regression, the regression coefficients can be estimated by

$$b_n = (X'X)^{-1}X'Y.$$

Before the first graded pair is presented to the respondent, the matrix X is set to the identity matrix. The vectors b and Y are set to the preliminary estimates from the self-explicated task. For the first updating the layout of the regression is expanded to

$$\begin{bmatrix} X \\ z' \end{bmatrix} b_{n+1} \sim \begin{bmatrix} Y \\ r \end{bmatrix}.$$

Into the vector z the presented attribute levels are coded. An element is set to 1 if the corresponding level appeared in the partial profile on the right of the screen, -1 if in the partial profile on the left of the screen, and 0 if it did not appear in either one. The response vector r is coded with values from +4 to -4 according to the position of the slider as set by the respondent, as for example in Figure 5.6. A positive value represents an offset to the right, a negative value to the left, and 0 means indifference (Sawtooth Software Inc., 2002). With the expanded layout the updated the updated regression coefficients b_{n+1} can be computed.

The presentation of graded-pairs is continued until a specified goodness-of-fit threshold is reached or a maximum number of pairs are rated. As proposed by Johnson (1987), the recommended number of pairs in jAC is $3 \cdot (N - n - 1) - N$, where N is the number of levels of all attributes and n the number of attributes.

An important issue in phase III is the selection of the partial profiles to be presented to the respondent. The selection has two main objectives. First, the observations obtained from the pairs should be spread as evenly as possible over all attribute levels, and the columns of the design matrix should be as orthogonal as possible. Second, pairs should be chosen nearly equal in attractiveness.

This can be achieved as follows (Sawtooth Software Inc., 2002):

1. Count the number of times each pair of attributes has appeared together in any concept. Pick a set of attributes at random from among those whose members have previously appeared together the fewest times.

2. For each of the chosen attributes, repeat similar logic to find levels that have been paired least frequently.

3. Examine all possible ways of combining these levels into concepts. Find the pair of concepts most nearly equal in attractiveness, using the current estimates of the respondent's utilities.

4. Randomly determine which concept will appear on each side of the screen.

In the pairs section of ACA the partial product profiles are described on two to three attributes. Empirical work has shown that this is best practice, and little is gained from displaying partial profiles described on more attributes (e.g., Agarwal (1989)). The use of two to three attributes is also suggested in the Sawtooth's ACA technical paper (Sawtooth Software Inc., 2002).

The use of partial profiles in the pairs section implies a strong "all else equal" context, that is, the omitted attributes are supposed to have some level which is equal for both partial profiles. This is often criticized to be an unrealistic scenario for the respondents because real product profiles are rarely described and varied on two to three attributes only (Green et al., 1991). However, the problem of unrealistic scenarios does not occur in the example with the mobile phone accessories, because attributes not shown in the paired comparison task are simply assumed to be absent.

5.7 Integrating Estimation of Willingness-to-pay

The new estimation procedure for willingness-to-pay (PE scene), which is presented in Chapter 7, uses individual level preference structure as input. For this part-worths estimated by conjoint analysis are used.

The empirical investigation presented in Chapter 8 is carried out as an online survey. Therefore, the conjoint interview should not be too long, in order to achieve a high completion rate. ACA is especially designed to handle a large number of attributes, as it has the ability to reduce the number of questions the respondents are asked. It is therefore well suited for our empirical investigation.

ACA has successfully been implemented in many conjoint studies and was the most frequently chosen method in Europe (Wittink and Burhenne, 1994) and the USA in the 1990s (Orme, 2003). The advantage of ACA over other conjoint methods is that it is a combined presentation and estimation computer package. With a web-frontend it can be used for online surveying.

For our empirical investigation a software is needed which can easily be adapted, in order to integrate the new interview scene to estimate willingness-to-pay. The interviewing software used in our empirical investigation is a re-implementation of ACA called jAC (Schmidt-Thieme, 2004). The frame work is implemented in the Java^{TM}programming language and has a modular design. The modular design makes it easy to integrate new interview scenes. For our empirical investigation the calibration scene (phase IV) was replaced by the new PE scene.

Between the different interview scenes the data from all previous phases is passed along. At the end of the third phase, the part-worths for the attribute levels are already estimated. After this phase the part-worths are simply passed to the PE scene. The part-worths and the underlying attributes and levels are the only input the PE scene needs. Therefore, it is easy to omit the calibration scene, and replace it with the PE scene.

One of the most difficult things in designing a conjoint study after the attributes and levels have been selected properly is the wording and graphical presentation to the respondents. Thorough pretesting and discussion with testers is necessary to make sure the objective of the interview is anchored correctly in the respondents heads. This is all the more important for online interviews, because there is no interviewer supervising the interviewees. The powerful web-frontend of jAC has all the flexibility needed to position texts and graphics freely on the clients screen and provides interactive elements that make the interview interesting and entertaining.

5.8 Summary

In this chapter an overview of conjoint analysis was presented. The different methods were distinguished based upon a classification of their presentation techniques to the respondent. The different conjoint methods of the classification were introduced and compared with one another. A special focus was put on adaptive conjoint analysis (ACA), because this conjoint method is used in the empirical investigation of this thesis.

The empirical study is an online survey, hence it is important to keep it as short as possible. ACA has the ability to handle large number of attributes because it reduces the number of questions asked during the interview. Furthermore, it is a computer package, and has a web front-end. Because of these reasons, we chose to use ACA for our empirical investigation.

ACA consists of four phases, two self-explicated tasks, the adaptive part and a calibration scene. The four phases were discussed in detail. A special focus was laid on the selection of the product stimuli and the parameter estimation techniques in the adaptive part of ACA.

The calibration scene of ACA is not used in our empirical study, because it is replaced by the price estimation scene (PE scene). Nevertheless, the original calibration scene was also presented in this chapter. In this chapter it was shown how the PE scene is combined with ACA.

Screenshots from a re-implementation of ACA called jAC (Schmidt-Thieme, 2004) were presented. This re-implementation will also be used for the empirical investigation presented in Chapter 8. In the empirical investigation a new interview scene, in which willingness-to-pay is estimated, is integrated into ACA. It was outlined, how this is done with the jAC framework.

Chapter 6

Conjoint Analysis in Pricing Studies

This chapter discusses how pricing studies are performed when conjoint analysis is applied. The general approach is to include price in the conjoint study as yet another attribute. We will explain how this is done, and review a selection of publications which explicitly focus on the estimation of willingness-to-pay (WTP).

Subsequent to this it will be developed what problems can arise from traditional approaches when price is included as an attribute. Three problems that can be identified will be the main focus of attention. These are (1) theoretical problems, (2) practical problems, and (3) estimation problems. Each of these problems will be discussed in detail. These problems will be emphasized and it will be illustrated how they can be overcome when the new estimation approach, the PE scene, is applied.

6.1 Introduction

According to the literature pricing studies are one of the most important applications of conjoint analysis (e.g., Gustafsson et al. (2000, pp. 6-7)).

In a study on conjoint applications in the US in the years 1981-1985 Wittink and Cattin (1989) surveyed 59 companies who carried out 1062 conjoint studies. 38% of the identified studies were pricing studies. In a similar study on the application of conjoint analysis in the European market in the years 1986-1991 Wittink and Burhenne (1994) surveyed 66 companies and reported a total of 956 conjoint studies. Out of these 46% were pricing studies. Baier (1999) carried out a smaller study in the German market. 8 companies were interviewed and 382 conjoint studies were identified, of which 62% were pricing studies. Hartmann and Sattler (2002a,b) surveyed 54 marketing research institutes in Germany, Austria, and Switzerland in the year 2001. These institutes performed a total of 304 studies regarding preference measurement. 121 studies were documented in greater detail by the marketing research institutes, showing that 48% were pricing studies.

Not only surveys of the usage of conjoint analysis show the importance of pricing research. Publications of the application of conjoint analysis in scientific journals also illustrates their importance. In a broad review Voeth (1999) summarizes the publications on conjoint analysis in German between the years 1976-1998. Most of the identified 150 studies were published in the 1990s. 31 studies explicitly focused on pricing.

Some of the best examples from the literature regarding pricing studies performed by conjoint analysis in important German and English scientific journals are Currim et al. (1981), Mahajan et al. (1982), Goldberg et al. (1984), Green and Krieger (1990), Balderjahn (1991), Green and Krieger (1992), Balderjahn (1994), Eggenberger and Christof (1996), and Green et al. (1997). As can be seen from practical applications and journal publications, pricing studies are an important field of conjoint analysis. Apparently, conjoint analysis is a method which is well suited for pricing studies (Diller, 2000, p. 202).

In order to design a pricing strategy exceptionally insightful knowledge is needed regarding to the reaction of customers to different price schemes. Questions like the following must be answered: How many customers will buy a certain product at different price levels? What does the preference structure of the customers look like for different product configurations under different prices? Can variations of a specific feature for different products be assigned a monetary equivalent? Can customers be classified based upon their preference structure? With conjoint analysis researchers and marketing experts attempt to answer these questions.

The major approach in pricing studies by conjoint analysis is incorporating the price in the study as an additional attribute (e.g., Green and Srinivasan (1990), Orme (2001)). The levels of the attribute price are then assigned part-worth utilities like the other attributes, and relative utility differences between combinations of attributes can then be computed. For different part-worth utilities of price points interpolation heuristics are applied. For example consider an attribute price with two levels. Similar to other conjoint attributes, part-worths are estimated for the two price levels. Between the two price levels interpolation heuristics are applied estimating a utility for every price point between the two price levels.

With a utility score for every possible price the preference of the respondents for every product price combination can be computed. With the additional information which products the customers would actually buy (and not only prefer) the marketing questions stated above can be answered.

6.2 Selected Publication on the Estimation of Willingness-to-Pay

The following paragraphs discuss five publications in chronological order. These are the publications by Kohli and Mahajan (1991), Wübker and Mahajan (1999), Jedidi and Zhang (2002), Sattler and Nitschke (2003), and Backhaus and Brzoska (2004). The publications serve well to show the development in the estimation of willingness-to-pay by conjoint analysis over the past 15 years. In these studies the authors estimate willingness-to-pay from conjoint data which include price as an attribute.

Study 1 by Kohli and Mahajan (1991):

According to literature the first work explicitly focusing on the estimation of willingness-to-pay and using conjoint analysis is from Kohli and Mahajan (1991). The authors define willingness-to-pay as follows: "We assume that a consumer's reservation price for a new product is determined by his or her (estimated) utility for the product in relationship to the price and utility for his or her most preferred product among all product offerings in his or her evoked set". The consumer's evoked set is the unique choice between a number of products, of which one, and only one, can and will be purchased. The definition the authors used for reservation price corresponds to our definition of the maximum price in Section 3.1. The authors do not attempt to measure the economic reservation price how we defined it in Section 3.2.

Formally Kohli and Mahajan model the estimation of willingness-to-pay price based on conjoint data as follows:

$$u_{it|\sim p} + u_i(p) \geq u_i^* + \epsilon.$$

In this notation some individual i prefers some product t over some status quo product that has the utility u_i^*. The status quo product has the highest estimated utility of any currently available product in consumer i's evoked set. Product t is preferred if the sum of the part-worths of the non-price attributes $u_{it|\sim p}$ and the part-worth due to price $u_i(p)$ is higher than the utility of the status quo product plus some arbitrarily small number ϵ.

In the reminder of their work the authors assume that the observed WTPs are drawn from a normal distribution. They estimate this distribution and describe shares of preference for different products at different prices based upon the distribution's density function.

Kohli and Mahajan present an empirical application, in which they test different apartment concepts among MBA students. The preference structure for the concepts is estimated for each individual by conjoint analysis. Price is included as an attribute and modeled as a continuous linear variable in the multi-attribute preference function. A status quo apartment is assumed to be given at a fixed price. This status quo apartment is the same for every respondent. Against this apartment the prices for all other concepts at which the respondents would switch away are calculated.

Note, that the prerequisite for a correct forecast of a respondent's willingness-to-pay is that every respondent perceives the status quo apartment the best alternative in his or her evoked set. Furthermore, every respondent must be willing to accept the current price of the status quo apartment. Therefore, the estimated procedure as proposed by Kohli and Mahajan (1991) can only correctly predict price response behavior for respondents who would accept the status quo product.

Study 2 by Wübker and Mahajan (1999):

Wübker and Mahajan apply a reservation price model to a bundling scenario building upon the article of Kohli and Mahajan (1991). Their concept of reservation price also corresponds to the maximum price concept. In their work the authors extend the approach of Kohli and Mahajan by not only estimating willingness-to-pay for individual items, but

Attributes

	Price (DM)	Bundle
Levels	2.50	French Fries (large)
	5.00	Big Mac
	7.50	Drink (medium)
	9.00	Big Mac and French Fries
	10.50	French Fries, Big Mac and Drink

Table 6.1: Attributes and levels for bundle types and price used in a conjoint analysis at McDonald's restaurant by Wübker and Mahajan (1999).

also to estimate willingness-to-pay for product bundles.

The authors achieve this by viewing each product bundle as an individual item. For the different bundle types a conjoint design consisting only of the two attributes *bundle* and *price* is used. The levels of the attribute bundle are different bundle combinations, the level for the attribute price are a fitted pricing range for the different combinations. The definition of their attributes and levels is shown in Table 6.1.

Out of the 25 possible attribute level combinations the authors limit themselves to seven that seem feasible in order to avoid stimuli that are too cheap or too expensive. Wübker and Mahajan use adaptive conjoint analysis (ACA) to estimate the respondents' preference structure. Based upon the conjoint data a maximum price for the three-item bundle *French Fries, Big Mac and Drink* is calculated for each respondent such that he or she prefers that bundle over the consumption of any other bundle for which the price is set at the regular list price of McDonald's restaurant. For example if the most preferred choice in the evoked set was the two-item bundle *Big Mac and French Fries* at the regular price, the price for the bundle *French Fries, Big Mac and Drink* was altered such that the individual would prefer the three-item bundle.

An empirical study was carried out and for every price in the conjoint design a part-worth utility was estimated. Between the part-worths of the price levels interpolation heuristics were applied. This resulted in a piecewise linear relationship between utility and price. However, the authors did not present a justification on why piecewise interpolation was used.

Wübker and Mahajan compared the resulting maximum prices for different product bundles to self-stated willingness-to-pay elicited in a direct questioning. The authors find that self-stated willingness-to-pay yields higher values than the conjoint approach. They suspect this effect results from the isolated perception of price in the direct questioning, especially that no alternative alternative options (other bundles) were being offered.

Study 3 by Jedidi and Zhang (2002):

Jedidi and Zhang also develop upon the article of Kohli and Mahajan (1991) but depart in adopting a different definition of willingness-to-pay. They use the standard definition of consumer reservation price in economics. Furthermore, the authors dismiss the assumption of unconditional category purchase, with which they refer to the assumption that the introduction of a new product solely affects consumers within a purchase category. This means that they do not utilize the assumption that every respondent would accept a fixed status quo product. The assumption of unconditional category purchase does not hold when new products are introduced that attract consumers, who did not buy in that category before. The attracting of new consumers is called market-expansion.

Jedidi and Zhang define the reservation price in their work as "a consumer's reservation price for a specific product is simply the price at which the consumer is indifferent between buying and not buying the product, given the consumption alternatives available to the consumer". This definition corresponds with our definition of the reservation price and is different than our definition of the maximum price.

To our knowledge the Jedidi and Zhang are the first who have applied the concept reservation price in a conjoint study. They also emphasize this distinction between early work estimating maximum price and their approach by "they *(Kohli and Mahajan, 1991)* [italics added] define reservation price for a product as the maximum price the consumer is willing to pay to switch away from the most preferred choice in her evoked set to the product in question. Thus, a consumer's reservation price for a product depends not only on the additional value the product provides, but also on how much the consumer pays for her most preferred choice". According to the authors the assumption of a status quo product for each consumer facilitates the discussion. With this facilitation it cannot be assessed whether the price of a new product expands or contracts the market.

Formally, Jedidi and Zhang present the condition of the reservation price $r_i(P)$ that some individual i has for some product P as

$$U_i\Big(P, \frac{m_i - r_i(P)}{p_i^y}\Big) - U_i\Big(0, \frac{m_i}{p_i^y}\Big) \equiv 0.$$

As in economic theory the individual has a utility function $U_i(P, y_i)$ for the consumption of the product and the consumption of some amount of the composite product y_i. The amount of the composite product consumed by the individual is expressed in terms of a budget constraint $m_i = p_i^y y_i + p$ and the price p for product P.[1] Note that the authors allow the unit price p_i^y for the composite product y_i differ for each individual.

Jedidi and Zhang interpolate between the levels of the attributes and extrapolate to zero. The derived utility for the absence of the attribute is assigned zero monetary value. Offset to this utility score, the exchange rate between utility and price is applied to calculate the reservation prices.

This will be illustrated by an brief example with the attributes price and size of hard disc as shown in Table 6.2. The part-worths of the attribute levels are estimated by conjoint analysis.

The linear extrapolation of the size of hard drive to 0 GB leads to 5 utility units. This can

[1]Compare the excursion on economic theory and reservation price in Section 3.6.

Hard Disc	Part-Worth
100 GB	10
200 GB	15

Price	Part-Worth
500 €	10
100 €	50

Table 6.2: Example of attributes price and hard disc with assigned levels and estimated part-worths.

be seen in the upper part of Table 6.2. Since 5 utility units is equivalent to the absence of hard drive, the authors derive that the respondent would pay no money for 5 utility units. The exchange rate between utility and price in this example calculates to 10 € per utility unit ((500 € - 100 €) / (50 - 10) = 10). Using the exchange rate between utility and price and subtracting the utility for which the respondent would pay no money the authors calculate the reservation price for the levels of hard disc. For 100 GB hard drive the reservation price of the respondent would be 50 € (calculated by (10 - 5) · 10 € = 50 €). Jedidi and Zhang (2002) label their approach Augmented Conjoint Analysis.

The authors present an empirical study carried out amongst MBA students at a major U.S. university. The probands were presented a conjoint design for notebooks consisting of the attributes price, brand, memory, speed, and hard drive with either two or three levels. The data was collected with a traditional conjoint measurement method. Overall the sample consisted of 848 useable observations from 53 subjects.

For the market entry strategies *penetration*, *skimming*, and *product line* market share simulations were carried out. With a penetration strategy the market is entered with a low-cost product, skimming aims at the high price segment, and with a product line strategy two differentiated products are introduced at both ends of the possible price range. The simulation was performed for the entry with a new notebook (NNB) on a market with one existing notebook (ENB).

From the estimated conjoint coefficients a traditional market share simulation (Traditional MSS) was carried out and was compared with the augmented estimation approach (Augmented MSS) suggested by Jedidi and Zhang. Some of the results of the market share simulations for the three pricing strategies are shown in Table 6.3. With the price of the existing notebook held constant the optimal prices for the market entry strategies were used for the simulation.

The estimation of a reservation price permits the simulation of a no-purchase share (Augmented MSS). The no-purchase consists of the respondents who would buy neither notebook under the different pricing strategies. Traditional market share simulation (Traditional MSS) cannot estimate the fraction of customers who decline to purchase any of the product offerings.

As can be seen from the results in Table 6.3, the knowledge of reservation prices changes

	Traditional MSS		Augmented MSS		
	NNB	ENB	NNB	ENB	no purchase
Penetration	48,3%	51,7%	11,1%	38,9%	50,0%
Skimming	69,6%	30,4%	33,3%	18,5%	48,1%
Product Line	56,4%	23,6%	33,4%	18,5%	48,1%

Table 6.3: Comparison of traditional conjoint analysis with augmented approach (Jedidi and Zhang, 2002).

the division of the market between the new- and the old notebook substantially. Traditional MSS promises an appealing market share for a new notebook under a penetration strategy leading to a market share of 48,3%. However, traditional MSS cannot simulate the share of non-buyers but only the shares of customers for the new- and the existing notebook. With share of customers not buying any notebook, the use of a penetration strategy for the new notebook appears less promising. With augmented MSS the share of non-buyers is estimated to 50% and the share for the new notebook is estimated to only 11,1%.

In order to test the validity of their model Jedidi and Zhang compute the correlation between self-stated reservation prices and estimated reservation prices for the new product. They find a positive correlation between the two values across the consumer population.

Jedidi and Zhang have impressively shown the importance of the estimation of willingness-to-pay in market share simulations. In many use cases it is absolutely necessary to estimate the fraction of consumers who do not enter or leave the market under certain pricing strategies. Without this knowledge the possibility of large forecasting errors can occur.

However, the authors reuse conjoint data which does not include a decision rule. That is, the respondents are never asked whether they would really purchase a certain product at a specific price. The dataset resulting from the conjoint analysis is enriched with the assumption of choice behavior through the use of interpolation heuristics.

Study 4 by Sattler and Nitschke (2003):

Sattler and Nitschke elicit willingness-to-pay by conjoint analysis similar to Kohli and Mahajan (1991). But instead of assuming the same status quo product for each participant on the conjoint study, the respondents are asked to indicate which products they would actually purchase at a given price. This is done by the Limit-conjoint procedure proposed by Voeth and Hahn (1998) which was already mentioned in Section 4.5.1. In this procedure price is included as an attribute in the conjoint study. First a standard conjoint analysis is performed. At the end each respondent is asked to rank the presented product stimuli and to indicate which of the offers he or she would actually purchase at the given price. The offer that yields the lowest utility and is still marked as having potential for purchase by the respondent is considered to be the limit of the products, the respondent is willing to accept. Sattler and Nitschke then use this limit as the status quo product. As do Kohli and Mahajan (1991), the authors calculate prices for all product combinations such that they yield the same utility as the status quo product. These prices are then considered to be the willingness-to-pay for each product.

Letting every respondent indicate his or her own status quo product, Sattler and Nitschke have added a choice rule to conjoint analysis. Therefore, they need not use interpolation heuristics to find a utility value that yield a monetary equivalent as was suggested by Jedidi and Zhang (2002).

Sattler and Nitschke test the described conjoint procedure against the direct elicitation of willingness-to-pay, and find minor differences. More important, they could not find a systematic deviation in the same direction. For some products the self stated willingness-to-pay was higher than derived from conjoint data, for other products it was lower.

Study 5 by Backhaus and Brzoska (2004):

The last empirical investigation on willingness-to-pay presented here is a study by Backhaus and Brzoska (2004). They tested the Limit-conjoint procedure as used by Sattler and Nitschke (2003) and a choice based approach for external validity. This was different to the other studies, in which only internal validity was tested by comparing the estimations of willingness-to-pay by the conjoint procedures with self-stated willingness-to-pay.

With both estimation methods price response functions were estimated. In order to test external validity the authors performed an auction with the respondents, in which the products of the studies were sold. From this revealed purchase behavior also price response functions were estimated and compared to the price response functions based on the other two methods. The revealed purchase behavior was used as external validity measurement.

The results of their study indicate that the Limit-conjoint approach as well as the choice based approach yield low external validity. For both price response behavior for the tested products is over-predicted. The conjoint approach yields better external validity than the choice based approach at the aggregate level. However, at the individual level the conjoint approach over- and under-estimates the respondents' willingness-to-pay compared to the revealed behavior in the auction. It remains unclear whether the better predictive validity of the conjoint analysis at the aggregate level stems from over- and under-estimation of willingness-to-pay averaging one another out at the aggregate level.

However, the empirical evidence Backhaus and Brzoska provide is discomforting for the research on surveying techniques for willingness-to-pay.

6.3 Identifying Problems of Current Approaches

In the last section it was shown how conjoint analysis is applied in pricing studies. In all studies price was incorporated in the conjoint design as an additional attribute. It is our opinion that this approach has some problems which will be discussed in the following. Our reasons for emphasizing these problems is that an alternative approach for the estimation of willingness-to-pay by conjoint analysis without including price in the conjoint study can be provided.

Including price as yet another attribute in conjoint analysis suffers from three problems:

1. *Theoretical Problem*: By treating price as an attribute in a conjoint study part-worth utilities are estimated for the presented price levels. By definition price does not have a utility, rather it reflects an exchange rate between different utility scales, implying, the price of goods do not influence the goods' utility. Rather, it denotes how much of alternative consumption (with the associated utility) has to be given up to consume the good.

2. *Practical Problem*: The inclusion of price leads to several unwanted effects. In a conjoint study the occurrence of interactions between price and other attributes are likely to occur that violate the additive-compensatory model. Further crucial effects are the *price effect*, the *range effect*, the *number of levels effect* that occurs when price is included as an attribute. Last but not least, problems calculating the interpolation heuristics between utility and price can occur, when more than two price levels are used.

3. *Estimation Problem*: Traditional conjoint analysis does not incorporate a decision rule. That is, only preference structure is estimated and not choices for or against different products. When the objective is to estimate willingness-to-pay, researchers need choice information. This information is usually added to the data by assuming or explicitly asking the respondents for a status quo product with an associated willingness-to-pay. This might not be sufficient for an accurate estimation.

6.3.1 Theoretical Problems

In neoclassical economic theory of consumer behavior price is treated as an exogenous variable. It bears no more information to a customer besides how many units of different goods he or she may consume before the budget is exhausted. This treatment of price permits the construction of choice behavior and indifference curves as well as demand functions. In these neoclassical approaches price enters any model solely through a budget constraint (cf. Varian (2003, chap. 5-6)).

Nevertheless, besides an allocative function of the budget constraint, price does bear some kind of information to the customer. Price provides evidence of quality, as was first documented by Scitovsky (1945). On this topic a great number of empirical studies have been carried out, an overview is given in Rao (1993). These studies indicate mixed relationships between quality and price. A very low price might be perceived as an indicator of low quality, vice versa a very high price might be perceived as an indicator for high quality.

There also exist goods for which the allocative effect of price is reversed. For these products preference for buying increases as a direct function of price. They are called *Veblen goods*, examples are expensive wines and perfumes. Decreasing their prices decreases consumers' preference for buying them because they are no longer perceived as exclusive or high status products (Leibenstein, 1950). However, these types of products are not considered in this work.

In general this dissertation does not focus on the informational effect of price. Instead, focus is placed on the estimation of the willingness-to-pay consumers have for "normal" products. If some product is priced above some customer's willingness-to-pay, it might bear some positive quality signal, but the customer will not buy it.

As was shown in the previous chapter, when conjoint analysis is used in pricing studies for general consumer goods the common approach is to include price as an attribute of the study. For the different price levels used in the study, part-worths are estimated. Preference structure for different products at different prices can then be estimated.

By assigning part-worths utilities to the price levels of the study, price is treated fundamentally different than in neoclassical economic theory. Rao and Gautschi (1982) emphasized the distinction economists and conjoint analysts make with regard to the treatment of price. The approach of the latter is data-based rather than theory-based. The conjoint analyst would simply treat price as another attribute in the multi-attribute utility function because it makes estimation of response behavior simple.

Srinivasan (1982) responded to the argumentation of Rao and Gautschi (1982) that the distinct treatment of price is not so great after all and should not cause theoretical problems. When willingness-to-pay is determined by the reservation price, measured utility can be expressed in terms of price (cf. Section 3.2). With the reservation price determining a consumer's choice behavior, the consumption of the product reduces the amount of money that can be spent on all other goods subject to a budget constraint. Consuming less of the composite good reduces the consumers' derived utility from consuming the composite good. Using this argument the utility function of two goods, the good of interest and the composite good, can be re-arranged into a utility function of only the good of interest with price included as an attribute that attaches value to the product (cf. Ratchford (1979) and Srinivasan (1982)). Using this argument researchers treat price as an attribute in multi-attribute preference measurement.

However, here it is believed that willingness-to-pay for a product is seldom determined solely by the reservation price. Often it is determined by the maximum price (cf. Section 3.1). Under this concept the argument of Srinivasan appears not to hold. Under maximum price a product is viewed in comparison to perceived alternative offerings, so-called reference products. When the price of the best alternative offered changes, the willingness-to-pay for the product in question also changes. However, the utility of the composite good remains unchanged.

6.3.2 Practical Problems

When price is included in a conjoint study, the respondent is asked to rank, order, or compare different product configurations which have a price assigned. It is possible that some of these product configurations have an unfairly high price to some respondents or appear to be a very good deal. When this happens the respondents fail to compare this stimulus with other stimuli. This would lead to a non consistent ranking or rating. These stimuli would be rated artificially low or high. If this happens, the additive-compensatory model is violated and interactions between certain price levels with other attribute levels have occurred. This is likely to happen in a conjoint study with price as an attribute (Weiber and Rosendahl, 1997).

The *price effect* occurs when the number of attributes becomes large. In conjoint studies with many attributes of which one is price the importance of price tends to be understated, and the degree of understatement increases as the number of attributes increases (Orme, 2003).

Practitioners attempt to overcome this problem by calibrating the importance of price in a post process. In such a post process a number of product profiles are presented of which the respondents are asked to select their preferred choice. The most preferred choice is also predicted based on the utility scores estimated by the conjoint analysis. When some of the predictions fail, the importance of the attribute price is re-scaled by some factor. This factor is simply a positive number with which each price part-worth is multiplied. The factor is chosen such that the hit rate of the predictions is increased. One of the identified sources of the price effect is that respondents cannot process more than six attributes. Attributes are assumed to contribute additively to the utility of the product profile. When the respondent cannot process all presented attributes, the additivity of the underlying model is violated (Williams and Kilroy, 2000).

The *range effect* is a well studied effect in psychophysics (e.g., Parducci (1974)). If the physical range of attribute levels in an experiment is altered, the range of the stimuli responses is also altered (Verlegh et al., 2002). This is important for price, because price does not have a natural upper or lower limit. In a traditional price study using conjoint analysis determining the range of acceptable prices is crucial. Choosing a price range that is very wide, covering all possible prices, the resulting importance of the attribute price will be larger, than if a narrow range was chosen.

Another important effect in conjoint analysis is the *number-of-levels effect*. This effect in conjoint analysis has been studied by many authors (e.g., Wittink et al. (1989) and Steenkamp and Wittnik (1994)). Increasing the number of levels of an attribute increases the attributes importance significantly (Green and Srinivasan, 1990). The number-of-levels effect is even stronger than the range effect (Verlegh et al., 2002). Again, since price does not have a natural number of levels, the conjoint analyst must decide how many levels to use. In many incidences certain price levels are of special interest to a researcher. In such a case the researcher faces the dilemma that inserting the intermediate levels of interest, increases the estimated importance of price. Green and Srinivasan (1990) assume that the number-of-levels effect stems from an increase of attention towards attributes with more levels. Another explanation could be that respondents tend to distribute ratings of levels uniformly over a fixed mental response scale. Then, increasing the number of levels increases the amount of the scale used (Verlegh et al., 2002).

The price effect, the range effect, and the number-of-levels effect cannot be avoided for price, when it is included as an attribute in a conjoint study.

Attribute levels	Part-worths
Feature X	3
Feature Y	2
10 €	4
15 €	2
20 €	1

Table 6.4: Example with three price levels.

Another problem occurs by using more than two price levels. The estimation procedure for attribute level parameters is usually not constrained to support a natural ordering of the levels. But price has a natural ordering - a higher price level should have a lower part-worth than a lower price level. In unconstrained estimation it is possible and sometimes expected that the natural ordering of part-worths of price levels contains reversals (Orme, 2001) . Practitioners get around this problems by using as few levels as possible. When designing a conjoint study with price as an attribute Orme (2002) advises: "It's usually better to have more data at each price point than to have thinner measurements at more price points. Measuring too many points along a quantitative function can result in troublesome reversals. If you cover the entire range of interest with fewer levels, you can interpolate between levels...".

If more than two price levels are used, it is often difficult to decide how interpolation heuristics should be applied to estimate an exchange rate between utility and price. This will be illustrated by a small example. Suppose a conjoint analysis with two binary non-price attributes called feature X and feature Y which can either be present or absent. Part-worths are estimated for the features. Let the absence of any of the two features have a part-worth of zero. Another attribute is price which has three levels. The part-worths for features X and Y as well as for the price levels are given in Table 6.4

The change in utility between the first two price levels (10,- € and 15,- €) is 2 (4 - 2). Using this value to compute the exchange rate between price and utility results in 2,50 € per utility unit (5,- € / 2). Applying this exchange rate the monetary equivalent for the inclusion of the features X and Y can be computed. The inclusion of feature X is worth 7,50 € (3 · 3,50 €). The inclusion of feature Y is worth 5,- €.

If the change in utility between the second and the third price level (15,- € and 20,- €) is used, an exchange rate of 5,- € per utility unit is calculated. This exchange rate leads to different estimated monetary valuations for the inclusion of the features X and Y. If the endpoints of the price scale are used, that is the first and the third price level (10,- € and 20,- €), even another the exchange rate can be calculated, which is 3,33 € per utility unit.

If more than two price levels are used, the researcher cannot decide which exchange rate best fits the true valuation of the respondents. A common solution when more than two price levels are used is to analyze the utility of price using a single coefficient assuming that the price relationship is approximately linear (Orme, 2001). This results in one single interpolation heuristic. With this approach the decision problem regarding which interpolation heuristic to use is avoided.

6.3.3 Estimation Problems

Traditional conjoint analysis does not include a way to estimate choice behavior. In particular, the respondent cannot indicate that he or she would refuse to accept an offer at a certain price level, even though he or she would prefer that offer over others. Indication of refusal to accept is explicitly present in discrete choice analysis and is presented to the respondent as a no-purchase option. Forecasting choice behavior based on conjoint data can only hypothesize that a respondent would actually purchase one of the product stimuli at a certain price level. If the respondent was really willing to purchase in the category of studied products, a new product stimulus could be assigned a price, such that the respondent would choose that product over his or her most preferred alternative. This was done in the empirical study by Kohli and Mahajan (1991) which was presented in Section 6.2.

A product category is also referred to as a product class, in a sense that the utility from consumption in that class is additive separable from all other consumption (Strotz, 1957). Offsetting a price to the most attractive offering in a category is common practice in pricing studies (e.g., Balderjahn (2003) and Venkatesh and Mahajan (1993)). If the researcher does not know whether the respondent would actually purchase in that category, the conjoint data cannot be used to mimic market behavior (cf. Balderjahn (1993) and Weiber and Rosendahl (1997)).

Recently a variation of conjoint analysis was introduced in which every respondent is directly asked to indicate which product stimuli with assigned price would actually be considered for purchasing (Voeth and Hahn, 1998). This is done with a so-called "Limit-card" which is positioned in the rank order based on the utility scores of the product stimuli. This card marks the position above which the respondent would purchase the offering at the assigned price and below which he or she would refuse to purchase . This approach was used in the empirical investigations by Sattler et al. (2001) and Backhaus and Brzoska (2004), also presented in Section 6.2.

However, the estimation of the exchange rate between utility and price for all product stimuli and the all possible prices only relies on one indicated status quo product. This is the product just above the Limit-card. We believe that it would be better to elicit more data points in order to fit the exchange rate between utility and price. Therefore we will propose a method that uses more than one status quo product in order to predict the willingness-to-pay for all other products.

6.4 Summary

In this chapter short comings of pricing studies by means of conjoint analysis were thoroughly discussed beginning with presenting five empirical investigations on willingness-to-pay by conjoint analysis that illustrate recent developments in this field.

The general approach in pricing studies with conjoint analysis is to include price in the conjoint design as yet another attribute. This approach suffers from three problems which have been discussed in detail. The reason for emphasizing the problems that occur from including price as an attribute is that we propose a new method to estimate willingness-to-pay which is also based on a conjoint analysis, but in which price is not included as an attribute.

The identified problems are firstly theoretical problems, secondly practical problems, and thirdly estimation problems. Each one is summarized in the following:

(1) By treating price as an attribute in a conjoint study part-worths are estimated for the presented price levels as for the other attributes. By definition the price of a product does not have a utility, rather it reflects the foregone alternative consumption (with the associated utility) if the product is purchased.

(2) For practical application the inclusion of price might have several unwanted effects. These are the price effect, the range effect, the number of levels effect, and the occurrence of interactions between price and other attributes. These effects were discussed and illustrated with small examples. It was further shown that the application of interpolation between different price levels can be difficult if more than two price levels are used in the conjoint study.

(3) Traditional conjoint analysis does not incorporate a decision rule. Without a decision rule actual purchase behavior can only be hypothesized. Recently, the estimation of choice behavior was added to conjoint analysis by letting the respondents indicate which products they would actually consider for purchasing. However, this approach delivers only one data point. This data point is a single product for which the willingness-to-pay is known. Based on this data point the willingness-to-pay is estimated for all other products. We have argued that one data point might not provide enough information.

Chapter 7

Price Estimation Scene (PE Scene)

In this chapter a novel approach to estimate willingness-to-pay (WTP) is presented. In previous chapters it has been established that it is important to have a surveying instrument that can estimate willingness-to-pay at the individual level based on each respondent's provided information only. The method is as an additional interview scene which is an extension to conjoint analysis. We call this new interview scene "Price Estimation Scene" (PE scene).

However, in the preceding conjoint analysis price is not incorporate as an attribute. For the configured products of the study the conjoint interview is only used to estimate each respondent's preference structure based on the non-price attributes. In Chapter 5 it was demonstrated that conjoint analysis is a well suited instrument to provide such a preference structure for different product configurations. The outcome of conjoint analysis are cardinally scaled utility scores for all product configurations that can be formed by the configured attributes and levels.

By not having to incorporate price as another attribute in the conjoint analysis, the problems that arise from the inclusion of price are avoided as discussed in detail in Chapter 6.

In the PE scene a function is estimated that maps the utility scores from the conjoint analysis on a price scale. With this function the willingness-to-pay for any product that can be formed by the attributes of the conjoint study can be calculated. This is done by inserting the product's associated utility value in the function.

With the PE scene the problem is overcome that conjoint analysis does not incorporate a decision rule: The new scene is realized as a choice scene, similar to discrete choice analysis.

7.1 Presentation to the Respondent

In the PE scene every respondent is presented a series of screens. A single screen consists of a full product stimulus with an assigned price. The product stimulus is presented with full textual and graphical information about the product offered to mimic a real purchase

Figure 7.1: Example: Screenshot of a PE Scene.

situation as close as possible. The respondent is asked to indicate if he or she would actually purchase the product at the given price.

By allowing the respondent to indicate whether a product stimulus at an assigned price is acceptable, the problem of a missing decision rule in pricing studies with conjoint analysis is overcome as was also discussed in the previous chapter.

The respondent is presented a number of screens with different product profiles at dynamically set prices. Every time, the respondent has the option to take the offer or leave it. An example of a screen in the PE scene, similar to the ones used in the empirical study discussed in Chapter 8, is shown in Figure 7.1. In this figure the respondent is presented a product bundle consisting of a telephone NOKIA 6220, an extra rechargeable battery, and an additional battery charger station. The price for the bundle is dynamically set to 110,49 € based on the utility estimations from the preceding conjoint analysis. The respondent indicates whether the offer is acceptable or not by clicking on one of the buttons below the stimulus.

In every PE scene the respondent provides information whether he or she accepts a product at a given price or refuses to accept it. If the respondent refuses the product, an upper bound for price at the current utility level of the product range is found. If the respondent accepts the product in a PE scene, a lower bound for price at the given utility level is found.

For example, if the respondent did not accept a product stimulus at a certain price he or she would also refuse to accept any other product that only yields the same utility or an even lower utility at the same price. Obviously, the respondent would also refuse to accept any product configuration with the same or a lower utility offered at a higher price. Therefore, the price which was marked as not acceptable is an upper bound for the current utility level.

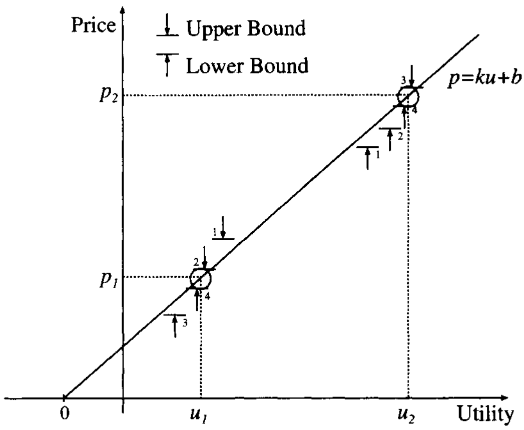


Figure 7.2: Estimation of a high and a low reservation price point in the PE scene from observed upper- or a lower bounds of the price (denoted by the arrows).

If the respondent accepted the price, a lower bound was found. He or she would also accept any lower price for a product configuration with the same or a higher utility.

7.2 Estimation of Willingness-to-Pay and Selection of Product Stimuli

With the sequence of screens in the PE scene we iteratively search for borders in the *utility* $\times$ *price* space. Upper and lower bounds for price and utility are narrowed to a desired accuracy. When the desired accuracy is reached, the middle between the bounds represents an estimation of the respondent's willingness-to-pay at that utility level. Any product at that utility level has this estimated willingness-to-pay. This means, for these products at the estimated willingness-to-pay, the respondent would be indifferent between accepting or refusing the offer. By this procedure one or many estimates for $\langle$*utility, price*$\rangle$-points that represent willingness-to-pay can be found.

Based upon the estimates found by the search procedure a model can be fitted that maps utility on price. As argued in Chapter 3, from a theoretical point of view the use of a linear model seems to be appropriate to describe the choice behavior of respondents.

The use of linear models is also a common approach in social sciences. For narrow ranges of observed values linear models produce a similar good fit as other models (Naert and Leeflang, 1978, pp. 66-67 and pp. 110-113). The assumption of a linear model for price is also common in pricing studies. In traditional conjoint analysis often a *vector model* is used to model continuous variables such as travel time or price (cf. Green and Srinivasan

```
find-reservationprice-point(u, p, Δu, Δp, Δp_stop, s_max,
i) :
b⁺ := (u⁺, p⁺) := ∅, b⁻ := (u⁻, p⁻) := ∅, j := 1
while b⁺ = ∅ or b⁻ = ∅ do
      if purchase(product(u), p)
        b⁻ := (u, p)
        (u, p) := (u + Δu, p + jΔp)
      else
          b⁺ := (u, p)
          (u, p) := (u − Δu, p − jΔp)
      fi
      j := j + i
od
while p⁺ − p⁻ > Δp_stop and s_max-- > 0 do
      (u, p) := (½(u⁻ + u⁺), ½(p⁻ + p⁺))
      if purchase(product(u), p)
        b⁻ := (u, p)
      else
          b⁺ := (u, p)
      fi
od
return (½(u⁻ + u⁺), ½(p⁻ + p⁺))
```

Figure 7.3: Search algorithm for a ⟨*utility, price*⟩-point.

(1978)). The vector model assumes a linear relationship between the attribute's levels and the estimated part-worths. When other models are applied such as the *part-worth model*, practitioners often use no more that two price levels and inter- and extrapolate between the two part-worths and thus obtain a linear relationship (e.g., Pinell (1994)). When more than two levels are used, practitioners often apply linear regression (cf. Orme (2001, 2002)). In all of these approaches the relationship between price and utility is assumed to be linear

In the PE scene a line with slope k and intercept b to describe the mapping of utility on price is estimated:

$$p = k \cdot u + b.$$

This is done by searching for two points in the *utility* × *price* space and interpolating a straight line. We chose to use a simple interpolation for our experiment, because for this only two points are required. The reason is that only a limited number of questions could be asked in the PE scene because our empirical investigation was realized as an uncontrolled online survey. Too many questions could lead to respondents fatigue and the discontinuation rate would be high. If more WTP-points are estimated, least squares

WTP	Data Cable	Extra Charger	Headset	Leather Bag
147,87 €	DKU-2	DCV-14	–	–
145,26 €	–	DCV-14	HDW-2	CNT-327
140,84 €	DKU-2	–	HS-3	–
139,64 €	–	ACP-12E	HS-3	CNT-327
139,39 €	–	ACP-12E	HDW-2	–
136,39 €	–	DCV-14	HS-3	CNT-327
136,13 €	–	DCV-14	HDW-2	–
131,92 €	DKU-2	–	–	CNT-327
130,52 €	–	ACP-12E	HS-3	–
127,26 €	–	DCV-14	HS-3	–
122,79 €	DKU-2	–	–	–
121,60 €	–	ACP-12E	–	CNT-327
120,18 €	–	–	HDW-2	CNT-327
118,34 €	–	DCV-14	–	CNT-327
112,47 €	–	ACP-12E	–	–
111,30 €	–	–	HS-3	CNT-327
111,05 €	–	–	HDW-2	–
109,21 €	–	DCV-14	–	–
102,18 €	–	–	HS-3	–
93,26 €	–	–	–	CNT-327
84,13 €	–	–	–	–

Table 7.1: Results for a sample proband.

fitting can be applied to estimate a linear model.

A graphical presentation of the search procedure for two points and the interpolation is presented in Figure 7.2. The information each respondent provides by accepting or refusing a product that has an estimated utility and assigned price is shown in the figure as an upper or lower bound. The numbers at the bounds denote the order in which products with corresponding utility and price were presented. The presentation of screens is continued until two $\langle$*utility, price*$\rangle$-points are estimated at a predefined accuracy. These points are $\langle u_1, p_1 \rangle$ and $\langle u_2, p_2 \rangle$ and the predefined accuracy is denoted by a circle. Between the two estimated points interpolation heuristics are applied resulting in the straight line.

Note that the intercept between the straight line and the abscissa is the absolute utility of 0. With the origin given all part-worth utilities from the conjoint analysis can be transformed onto a ratio-scale. This is possible because conjoint part-worths are unique to linear transformation only.

The detailed algorithm for the estimation of the willingness-to-pay for one product and one respondent is presented as a code fragment in Figure 7.3. The function $product(u)$ chooses the product configuration closest to a desired utility u from the list of all possible products. Function $purchase(product(u), p)$ asks whether the user would buy the product chosen by *product*(u) at a given price p.

The first while loop in Figure 7.3 starts with an initial guess (u, p). The algorithm tries to box the probands utility/price exchange ratio by locating an upper and a lower bound (b^+, b^-), for example a price point at which the proband would purchase for a given utility and one at which the proband would decline to purchase.

In the second loop of the algorithm this interval is gradually narrowed by a bisection search. The bisection search terminates when the found interval, in which the reservation price lies, is narrowed to a predefined accuracy Δp_{stop}. To limit the maximal number of purchasing decisions a participant has to make, a second termination condition restricts the algorithm to a predefined maximal number of search steps s_{max}.

The initial guesses for acceptable prices are necessary to give the search procedure a starting point. Optimally they are set by marketing experts of the product domain.

The possibility that the procedure influences the respondent's behavior needs attention. To avoid that the respondents notice that the algorithm attempts to narrow the price range for one product configuration, the order of the presented product combinations for the n $\langle$*utility, price*$\rangle$-points is randomized or alternated. For example, for two points the algorithm would alternate between high utility and low utility combinations. Furthermore, the respondents are explicitly asked to view each offer independently.

7.3 Example of one Respondent

The PE scene was implemented for an empirical study with the customers of the online-shop of Nokia in Germany. The goal of this study was to estimate willingness-to-pay for mobile phones with a contract bundled together with suitable telephone accessories. Once, a respondent has performed the conjoint analysis and the PE scene an estimate for the WTPs of all possible product combinations is obtained.

An example of the resulting WTPs of one respondent is given in Table 7.1. The table does not contain all possible bundle combinations of the underlying study but only a fraction, and this serves well for illustrative purpose. The attributes in the example are a "data cable" for the connection between the telephone and a computer, an "extra battery charger", a "headset", and a "leather bag" for the telephone to protect against impacts and scratches. Due to space limitation of the table another attribute "car accessories" was left out. All presented different attributes had a "none" level to denote the absence of the attribute. In Table 7.1 the non level is denoted with a dash, for the other levels the product name of the accessories are used. Each row in the table denotes one product bundle and in the first column the estimated willingness-to-pay is given.

Besides estimating the WTPs for the different bundles, the willingness-to-pay for a change in attribute level can also be calculated. If a none level for an attribute is configured, the willingness-to-pay for including different types of the attribute can be estimated. In addition the monetary difference in terms of willingness-to-pay between different types can be estimated.

	Attribute	Level 1	Level 2	Monetary exchange rate
1	Headset	–	HS-3	18,04 €
2	Headset	–	HDW-2	26,91 €
3	Headset	HS-3	HDW-2	8,87 €
4	Data Cable	–	DKU-2	38,66 €
5	Extra Charger	DCV-14	ACP-12E	3,25 €
6	Extra Charger	–	ACP-12E	28,33 €
7	Extra Charger	–	DCV-14	25,08 €
8	Leather Bag	–	CNT-327	9,12 €

Table 7.2: Monetary exchange for attribute levels of the sample proband.

The difference in monetary exchange rates for various level changes in the attributes is given in Table 7.2. For example, for the inclusion of a headset of type "HS-3" the proband is willing to pay an additional amount of 18,04 €. This can be seen from row 1 in the table. For a headset of type "HDW-2" the proband is willing to pay an additional amount of 26,91 €. Because the proband prefers headset "HDW-2" over headset "HS-3" he or she is willing to pay more for the former. Consequently, the proband is also willing to pay for the level change from the less preferred headset to the more preferred headset. This level change for the attribute headset from "HS-3" to "HDW-2" is worth 8,87 € to the proband. This can be seen from row 3 in the table. Note that this amount is equal to the difference in valuation between the inclusion of either one of the two headset types.

7.4 Summary

In this chapter a new approach to estimate willingness-to-pay was presented in detail. This approach is called PE scene and works as an extension to conjoint analysis. Unlike traditional conjoint approaches price is not included in the conjoint study as an attribute. Instead acceptable prices for the products of the conjoint study are estimated in the subsequent PE scene.

The problems that occur when price is included as an attribute in conjoint analysis, as discussed in Section 6.3, do not occur with our estimation procedure.

In the PE scene the respondents are presented a sequence of product choices with assigned prices and indicate whether they would actually purchase the presented product profiles. Product stimuli as well as price scales that are adapted for each proband to reflect individual choice behavior. It was described how the selection of profiles and the dynamic assignment of prices for each proband is achieved.

Currently, we are not aware of any other surveying method that dynamically assigns prices to product offerings. Either prices are predefined and assumed to be appropriate for all respondents, or the respondents are directly asked to indicate their willingness-to-pay.

A search procedure narrows the accurateness of the estimated willingness-to-pay for all products of the preceding conjoint study. The search procedure was outlined as a pseudocode. The result of the estimation is a linear function that maps utility scores on price. With this function the willingness-to-pay for any product can be estimated based on its utility score.

The empirical investigation presented in the Chapter 8 implemented the PE scene in the modular framework of the Java Adaptive Conjoint tool (jAC version 1.1, Schmidt-Thieme (2004)) which was introduced in Section 5.7.

Partial results of one sample respondent were presented in this chapter, to illustrate the type of estimation that can be achieved by our method.

We believe that this approach is superior to other techniques. Compared to directly asking the respondent his or her willingness-to-pay the cognitive overhead is reduced by offering the respondent products with an assigned price. Empirical investigations in pricing studies have shown that respondent feel more confident choosing from assigned prices than assigning prices themselves (Chernev, 2003).

Compared to approaches in which the prices are a priori fixed, the PE scene dynamically adapts the price scales to reflect different levels of WTPs of the respondents. By doing this, the problem is avoided that predefined prices might reflect the range of market prices, but still may be unacceptable for some respondents. This is an important aspect if not only customer switching effects but also market expansion effects are estimated (cf. Chapter 6).

Chapter 8

Empirical Investigation: Nokia study

The application of the Price Estimation scene (PE scene) in a real-world scenario is the main objective of this chapter. This was performed among the customers of the online shop of Nokia in Germany in October 2004. It will be illustrated how this PE scene delivers individual level estimations for willingness-to-pay (WTP) that can be used for market simulations. The goal of the simulations is to optimize bundling strategies for joint sales of a telephone with a contract and suitable accessories in the online shop.

Nokia offers the full product range of their products in the German online shop. In addition, the shop offers telephone contracts of all German mobile telephone net operators and providers. Lately, the shop has introduced bundled sales of a telephone with a contract and suitable telephone accessories. At the time of the investigation, the online shop offered three different product bundles:

The first bundle consisted of a NOKIA 5140 telephone with a "D2 Vodafone - Minutenpaket 100" contract. Bundled with this, the shop offered the battery charger cable "LCH-12" for the use in cars via the cigarette lighter, a stylish NOKIA key fob, and the exemption of shipping costs. The sum of the prices of the components was 89,50 €. The bundle was offered at a discounted price of 79,- €.

The second bundle consisted of a NOKIA 6230 telephone and a "D1 - Relax 100" contract, a leather case "CNT-327" for telephones, a stylish NOKIA key fob, and the exemption of shipping costs are offered. The price of all components was 78,95 €. The bundle was offered at 69,- €.

The last bundle consisted of a NOKIA 3220 with a "O2 Genion" contract. Bundled with this the shop offered the radio headset "HS-2R", the battery charger cable "LCH-12", a stylish NOKIA key fob, and the exemption of shipping costs. The full price for the bundle was 47,50 €, the discounted price was set to 1,- €.

Conjoint Design I (Telephone NOKIA 3220 with "O2 Genion" contract):

Data cable	**Additional battery charger**	**Car charger cable**	**Headset**
• DKU-5 • without	• ACP-12E • without	• LCH-12 • without	• HS-2R • HDS-10 • HS-5 • without

Conjoint Design II (Telephone NOKIA 5140 with "D2 Vodafone - Minutenpaket 100" contract):

Data cable	**Additional battery charger**	**Car charger cable**	**Headset**
• DKU-5 • without	• ACP-12E • without	• LCH-12 • without	• HS-10 • HDS-3 • HS-5 • without

Conjoint Design III (Telephone NOKIA 6230 with "D1 Relax 100" contract):

Data cable	**Additional battery charger**	**Car Accessoires**	**Headset**	**Leather case**
• DKU-2 • without	• DCV-14 • ACP-12E • without	• MBC-15S • LCH-12 • without	• HDW-2 • HS-3 • without	• CNT-327 • without

Table 8.1: Attributes and levels of the three conjoint interviews for the different telephones and contracts.

In order to design bundling strategies for telephones with the contracts the marketing experts of the online shop are confronted with two important questions:

1. What components should be bundled with the telephones and contracts.
2. At what prices should the bundles be offered.

The objective of the marketing strategies can be to maximize sales, for example to promote a certain telephone, to increase customer satisfaction, or to maximize profits.

The prices for the three bundles described above were set manually by marketing experts of the online-shop. The bundles were composed and priced in view of the cost structure and possible profits of the components and in view of alternative offerings in the market.

There exist many more telephones and contracts that could be bundled with different accessories. However, in our study we focused on the telephones and contracts described above and investigated how different accessories bundled with the telephones and contracts offered at different prices would affect profit and sales.

In order to optimize the bundling strategies for the Nokia online shop a surveying technique was the only feasible alternative. It was not possible to test all bundle combinations at various price levels in a field experiment, because there exist too many possible bundles.

To estimate the attractiveness of different product bundles conjoint analysis can be used (e.g., Wübker and Mahajan (1999)). In order to not only estimate the preference structure of the customers for different bundles, but also translate this preference structure in willingness-to-pay (WTP), the price estimation extension for conjoint analysis presented in Chapter 7 is used.

The use of this scene allows the identification of customers who would accept certain bundles at specific price levels. This individual level information of the respondents is used to forecast shares of customers that would accept or refuse to buy a bundle. When different bundles are presented, it can be identified which one each individual would choose if the prices of the bundles were acceptable. The information from this type of simulations of the customers' price response behavior can be used to optimize the bundling strategies in the Nokia online shop.

For the interview the jAC framework developed by Schmidt-Thieme (2004) in which we have integrated the PE scene was used. This framework implements an adaptive conjoint analysis as described in Section 5.6. The framework has a powerful web-frontend which is well suited to perform the survey with the customers of the online shop.

8.1 Conjoint Design

Three different conjoint interviews were performed. For each of the telephones with contracts that are offered as bundles with accessories one interview is implemented. In each of the three interviews the telephone, the contract, and the shipping costs were held constant. The components of the product bundle other than telephone, contract, and shipping costs were coded as conjoint attributes. All possible accessories for the telephones being offered were included in the conjoint interview. By including all possible accessories the product bundles already for sale in the online shop were also tested. All attributes have a level with value "without" to denote its absence. Since all attributes represent additional accessories, a bundle of any combination of attributes makes sense to the respondent. The attributes and levels for the three interviews are given in Table 8.1.

The attributes support an additive compensatory model and are well suited for conjoint analysis: The attributes are independent of one another and contribute differently to the overall valuation of the product bundles. All attributes are relevant to the respondents and can easily be changed by the online retailer. All telephone accessories are often sold, and any bundled product combination can quickly be offered in the online shop.

Non of the attribute levels could possibly be unacceptable, at worst a respondent would assign some telephone accessories no valuation (he or she would be indifferent between having the item or not). There is no redundancy in the attributes, so double counting is avoided in the self-explicated part (cf. Green and Srinivasan (1990)). The duration of the interview is about 10 minutes which seems to be well suited for an uncontrolled online survey.

8.2 Online Interview

Out of a much larger customer base 1000 of the newsletter recipients were randomly selected and invited to participate in the interview. The respondents were contacted via a newsletter e-mail and directed to the online interview. A screenshot of the HTML-newsletter is shown in Figure 8.1.

As an incentive to participate the respondents were offered a 10,- € voucher for the Nokia online shop if they finished the interview. The voucher would be given to the respondents at the end of the interview. Additionally, the respondents automatically participated in a lottery in which they could win attractive prices from the online shop. Each e-mail sent to one of the 1000 participants had an unique link pointing to the online survey. The link had a unique identifier encoded in the URL to prevent anyone to participate more than once.

On the first screen of the interview the participants were presented a selection page, where they could select one of three telephone types for the interview. These telephone types were the ones the online shop offered for bundled sales at the time of the interview.

The response behavior for the newsletter e-mails and the self-selection into the three interviews is given in Table 8.2. For the interview with telephone NOKIA 3220 a total 58 interviews were commenced. 61 interviews were commenced for the telephone NOKIA 5240. Undoubtedly the most attractive telephone of the three was the NOKIA 6230 as 206 respondents selected this option for their interview.

The response rate for 1000 sent e-mails was 33%. Compared to other surveying studies with contact via e-mail, (cf. Cobanoglu et al. (2001) and Kaplowitz et al. (2004)) this is a good response. We cannot tell whether all e-mails actually reached the respondents. It is possible that the response rate would be much higher, if only the e-mails actually delivered to the respondents were counted (Bachmann et al., 1999).

Since telephone NOKIA 6230 is the most popular choice, the data of this interview is analyzed in this thesis. For the 206 commenced interviews 156 were completed. Some of the completed interviews had to be dismissed due to idiosyncratic response behavior. The dataset of a respondent was rejected if one of the following response behaviors occurred:

1. In the PE scene the respondent accepted prices for product bundles that were more than 40% higher than the highest possible sum of the list prices of the components. This means that the respondent did not understand that a product bundle is a combination of products also available at list price, which is only worth buying if a discount on the sum of the list prices is given.

2. The respondent accepted any price for the product bundles presented in the PE scene. When this behavior occurs, the respondent attempted to complete the interview as quickly as possible without providing meaningful answers.


NOKIA
Connecting People
Der Online-Shop
NOKIA Online-Shop Aktuell

Herzlich willkommen, Herr Breidert!
Viel Vergnügen mit Ihrem aktuellen Nokia Online-Shop Newsletter.

Wir laden Sie zu unserer Online-Befragung ein!

Gutschein über 10 €
NOKIA Online-Shop

Sie wurden für unsere online Befragung ausgewählt. Um das Angebot im Online-Shop zu verbessern, benötigen wir Ihre Mithilfe. Bitte nehmen Sie an der online Befragung teil.

Die Befragung zu Produkten wird ca. 10-15 Minuten Ihrer Zeit in Anspruch nehmen. Sie erhalten als Dankeschön einen Gutschein im Wert von **10 EURO**. Den Gutschein können Sie im Nokia Online-Shop einlösen.

Alle eingeladenen Teilnehmer nehmen automatisch an unserer Verlosung mit tollen Preisen teil. Informationen zu den Preisen erhalten Sie am Ende der Befragung.

Um an der Befragung teilzunehmen, verfolgen Sie bitte folgenden Link:
Hier geht es zur Online-Befragung.

Wir freuen uns auf Ihre Teilnahme und wünschen Ihnen viel Spass!

Einstellungen ändern Abmelden Weiterempfehlen

Dies ist eine automatisch generierte Nachricht. Bitte antworten Sie hierauf nicht. Offizielle Kontaktdaten finden Sie auf www.nokia-online-shop.de.

Figure 8.1: Screenshot HTML newsletter, sent 4th October, 2004.

	NOKIA 3220	NOKIA 5140	NOKIA 6230	Total
Interviews started	58	67	206	331
Interviews completed	46 (79 %)	53 (79 %)	156 (77 %)	255 (77 %)
Response Rate	6 %	7 %	20 %	33 %
Response first day	62 %	64 %	57 %	59 %
Response second day	16 %	21 %	14 %	16 %
Dismissed interviews	9 (20 %)	11 (21 %)	47 (30 %)	67 (26 %)
Valid interviews	37 (80 %)	42 (79 %)	109 (70 %)	188 (74 %)

Table 8.2: Response behavior to newsletter invitation.

3. The respondent did not accept any price for the product bundles presented in the PE scene, even though the price was lowered to 1,- €. As before the respondent attempted to complete the interview as quickly as possible without providing meaningful answers.

Rejecting interviews based on these idiosyncratic response behaviors resulted in 109 out of 156 valid and meaningful datasets.

The newsletter with the link to the online survey was sent on a Monday late at night. As illustrated in Table 8.2, for the telephone NOKIA 6230 118 interviews were carried out the first day, 28 interviews the second day. The interviews were collected over a total period of 10 days. The response times for the telephones NOKIA 3220 and NOKIA 5140 showed similar behavior. Again, this seems reasonable response behavior for online surveying with contact via e-mail (cf. Bachmann et al. (1999) and Cobanoglu et al. (2001)).

For the interview the respondents were first presented with a short introduction and then a detailed description of the attributes and levels. Help pages with information about the attributes and levels were accessible to the respondents during the whole interview. After the introduction and description of the attributes and levels the respondents performed the conjoint interview. The calibration scene of the classical ACA interview was not used because the PE scene was appended to the ACA.

The result of the conjoint interview is the estimated preference structure for the product bundles for each respondent. This individual level information is passed to the PE scene which results in estimated WTPs for all possible product bundles.

8.3 Estimations of Willingness-to-Pay

The respondents' WTPs for the bundles from the interview with the telephone NOKIA 6230 were analyzed. The dataset contained the WTPs of 109 individuals for all possible bundle combinations containing the telephone NOKIA 6230, a "D1-Relax 100" contract, with suitable accessories. The number of possible product bundles is 108. All simulations in the following are based on the data from the 109 individuals and the 108 product

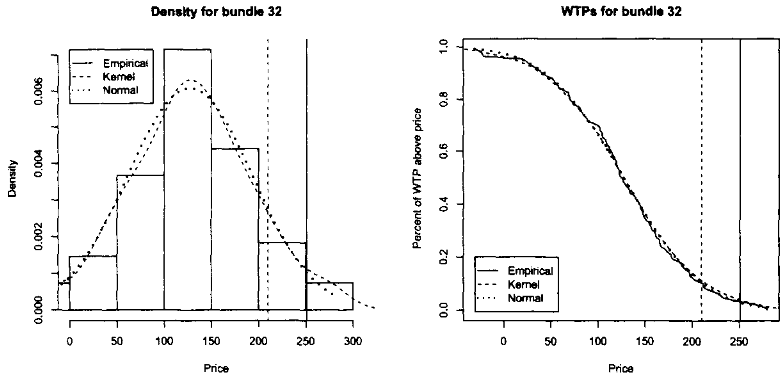


Figure 8.2: Density function and 1-cumulated distribution function of WTPs for bundle number 32.

bundles. The dataset was organized as a 109 $\times$ 108 matrix. The values of the matrix are the WTPs that each individual has for each product bundle.

For each of the possible product bundles the WTPs of the respondents were analyzed. The data of one specific product bundle is represented by the corresponding column in the data matrix. Each row in that column represents the willingness-to-pay of one individual for that bundle.

A kernel density function was estimated based on the observed WTPs. For this estimation a gaussian smoothing kernel was used. Furthermore, a normal density function was fitted to the WTPs. An example containing the plots of a histogram of the WTPs, the kernel density, and the normal density for one product bundle is given in Figure 8.2. The bundle in the example has the number 32 and consists of the telephone NOKIA 6230 with "D1-Relax 100" contract and the bundled components data cable "DKU-2", extra battery charger "ACP-12E", and headset "HDW-2".

For every price the percentage of individuals who had a higher willingness-to-pay was plotted. This plot is shown on the right side of Figure 8.2. In the same plot the estimated values from the kernel density and the normal density were added. Note that the plot for the estimated values of the normal density function is 1− the corresponding values of the cumulated distribution function.

In Figure 8.2 the empirical values are denoted by the solid line. This is the histogram on the left side and the solid downward-sloping line on the right side. The dashed lines on the right and the left side are plots based on the data of the kernel density function, and the dotted lines are the plots based on the normal density function. The solid vertical lines denote the list price for the sum of the components of the bundle dashed vertical lines denote the optimal price. The optimal price results in the highest possible profit

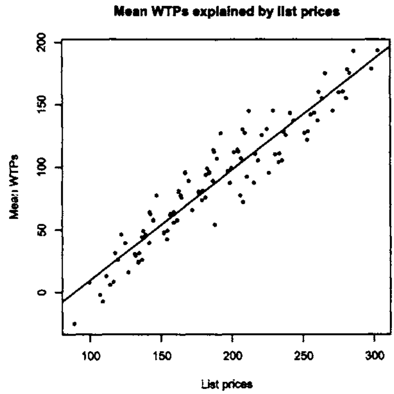


Figure 8.3: Linear Model: Mean WTP explained by list price

and is calculated from the empirical data. For bundle 32 the list price is 251,- € and the optimal price is 210,- €.

As can be seen from Figure 8.2 the estimations of the WTPs are very reasonable. At a price close to list price the percentage of respondents who have a greater willingness-to-pay approaches zero. This is consistent with the definition of the maximum price discussed in Section 3.1. Nobody would buy a product bundle if he or she could buy the components of the bundle separately at a lower price.

However, for some product bundles there is a small fraction of respondents that have an estimated willingness-to-pay that is slightly higher than the sum of the list prices. This can also be seen in Figure 8.2. Recall that the algorithm in the PE scene estimates the WTPs for all product bundles based on choice behavior of a much smaller number of bundles. Due to the estimation algorithm it can happen that some WTPs are estimated to higher values than the list price. For example, consider a respondent who chose to accept a price for a certain product bundle which was very close to the list price in the PE scene. Suppose the conjoint data contains a different bundle with a much higher preference that only has a slightly higher list price. If the respondent presented no choice behavior for this bundle in the PE scene, the algorithm could estimate a willingness-to-pay above the bundle's list price. Since the share of respondents with WTPs higher than the list price is very small and the WTPs are only slightly higher, we believe that the estimation procedure is robust.

It shows clearly in the dataset that the willingness-to-pay for the product bundles is highly influenced by the sum of the list prices of the components. The list prices are transparent in the online shop of Nokia. Therefore, they were also visible in the study during the conjoint analysis as well as during the PE scene. Using Pearson's correlation coefficient the correlation between the means of the WTPs of all respondents for the different bundles and the corresponding list prices has a value of 0.95. Spearman's ρ has a value of 0.95, Kendall's τ has a value of 0.82. A linear model having the WTPs explained by the list price was fitted. A plot of the fit is presented in Figure 8.3. Each point in the plot represents the mean of the WTPs of all respondents for one bundle which has a certain list price. It indicates that the list prices are well suited to explain the average WTPs of the customer population for the different bundles.

It seems that the respondents' WTPs are mostly determined by the maximum price and less by the reservation price. Recall from Chapter 3 that the reservation price is the price at which an individual is indifferent between consuming or not consuming the good. The reservation price does not depend on alternative purchase opportunities. Contrarily the maximum price for a product solely depends on the perceived price of the next best alternative plus the differentiation value to that alternative. In the mobile phone market perceived high discounts are very common.[1] The behavior seems to show that the respondents believe to find product bundles that are highly discounted from the list prices in the market.

In the literature willingness-to-pay for product bundles is often assumed to be normally distributed across the consumer population (e.g., Schmalensee (1984), Fürderer (1999), and Olderog and Skiera (2000)). Based upon the empirical evidence in our data we cannot prove this assumption to be wrong.

In order to test this the following null- and alternative hypothesis were formulated:

H_0 : The WTPs follow a normal distribution with mean and standard deviation of the empirical data.

H_a : The empirical data does not follow a normal distribution.

A Kolmogorov-Smirnov test for normality was performed on the WTPs of the different respondents for each of the bundles (Chakravarti et al., 1967, pp. 392-394). For bundle 32, which is shown in Figure 8.2, the p-value is 0.97 indicating that H_0 cannot be rejected. At a threshold for the p-value of 0.05 the fraction of bundles for which H_0 could not be rejected was 73 of 108. At a threshold of 0.01 the fraction is 101 out of 108.

To further test the null hypothesis a Shapiro-Wilk normality test was performed (Shapiro and Wilk, 1965). For bundle 32 H_0 cannot be rejected with a p-value of 0.78. At a threshold for the p-value of 0.05 H_0 could not be rejected for 31 out of 108 product bundles. At a threshold of 0.01 the fraction is 43 of 108.

8.4 Simulating Customer Choice Under Different Bundling Strategies

From the WTPs of the respondents as well as from the estimated distribution functions the units of the bundle sold, the resulting revenue and profit at each price can be simulated.

[1] High discounts are usually regained by rather expensive phone contracts with long-term policies.

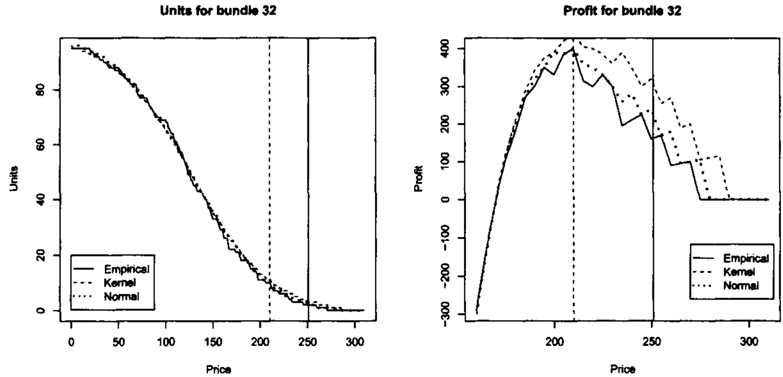


Figure 8.4: Units and profit for bundle number 32.

To simulate the units based on the empirical data, the number of individuals who have a willingness-to-pay which is higher than every possible price point was used. For the data based on the kernel density and the normal density function the units were simulated by taking the percentage of the individuals with higher WTPs than the possible price points times the number of individuals of the sample.

The revenue for the bundles offered at each price could easily be calculated by taking the estimated number of individuals accepting the price times the price. Since the wholesale prices for the different products were provided, the profits for different price levels could also be simulated. The profit was calculated as the revenue at each price minus the sum of the wholesale prices of the components of the bundle.

In Figure 8.4 the units and the profit at different prices for bundle 32 from Section 8.3 are shown. Again the plots based on the empirical data are denoted by the solid lines. The dashed lines are the plots based on the kernel density function, the dotted line are the plots based on the normal density function.

The following sections present simulations for a number of different bundles that could be offered separately and simultaneously in the online-shop of Nokia in Germany. These simulations were performed based on the empirical data and not based on the data of the estimated kernel density and normal density function.

In the simulations each individual could choose one of the offered product bundles or choose none at all.

The choices the individuals make were simulated for three different bundling strategies:

1. Under a *pure unbundling* strategy all products are offered for separate sales at the list price. Under pure unbundling each customer can select a combination of products that best meets his or her needs. The price for a combination of products is the sum of the single list prices.

Bundle	Data cable	Additional battery charger	Car Accessoires	Headset	Leather case
26	DKU-2	ACP-12E	LCH-12	HDW-2	–
31	DKU-2	ACP-12E	–	HDW-2	CNT-327
49	DKU-2	–	–	HDW-2	CNT-327
64	-	DCV-14	LCH-12	HS-3	-
73	-	ACP-12E	MBC-15S	HDW-2	CNT-327
91	–	–	MBC-15S	HDW-2	CNT-327

Table 8.3: Contents of bundles 26, 31, 49, 64, 73, and 91.

2. Under a *pure bundling* strategy one or more different product combinations are offered for joint sales as a bundle. The products of these bundles cannot be purchased separately.

3. Under a *mixed bundling* strategy all products are offered for separate sales at list prices as under pure unbundling. At the same time one or more product bundles are offered at some discounted price. The price has to be discounted, because otherwise there would be no difference for the customers who can purchase all components of the bundle separately.

To illustrate how different bundling strategies can be profitably employed, results from 6 different bundles are analyzed in the following. These are the bundles with number 26, 31, 49, 64, 73, and 91. The content of the bundles is given in Table 8.3.

The density functions of the WTPs and the corresponding distribution in the population for the 6 bundles are shown in Figure 8.5 and 8.6. As in the Figures 8.2 and 8.4, the plots based on the empirical data are denoted by the solid lines. The dashed lines are the plots based on the kernel density function, the dotted lines are the plots based on the normal density function. The list prices for the sum of the components of the bundles are denoted by a vertical solid line. The optimal price is denoted by a vertical dashed line.

8.4.1 Maximizing Profits Under Different Bundling Strategies

Before the simulations are presented, the behavior of the consumers and the vendor of the product bundles needs to be described in greater detail. First the individuals' choice behavior when they are confronted with different bundles is defined. Second a maximization problem for the vendor of the bundles is formulated to find a pricing strategy that optimizes profits.

In all simulations every consumer i out of the customer space N can select at most one of the offered product bundles out of the bundle space B. The choice behavior of each individual i is described as a binary vector $\vec{\gamma_i} = (\gamma_{i,1};\ \ldots;\ \gamma_{i,B})^T$. Every consumer's WTPs for each of the bundles is denoted by the vector $\vec{WTP}_i = (\vec{WTP}_{i,1};\ \ldots;\ \vec{WTP}_{i,B})^T$. The vector of prices for the bundles, the individual is currently confronted with, is denoted

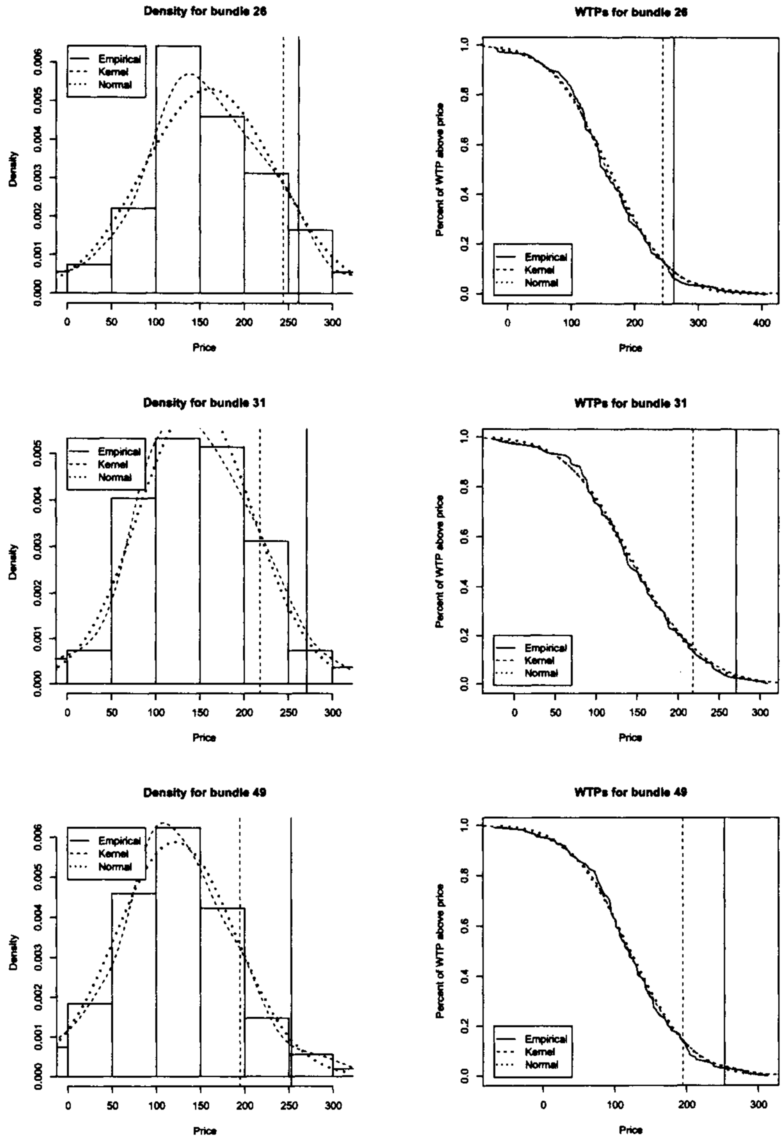


Figure 8.5: Density functions and 1-cumulated distribution functions of WTPs for bundles 26, 31, and 49.

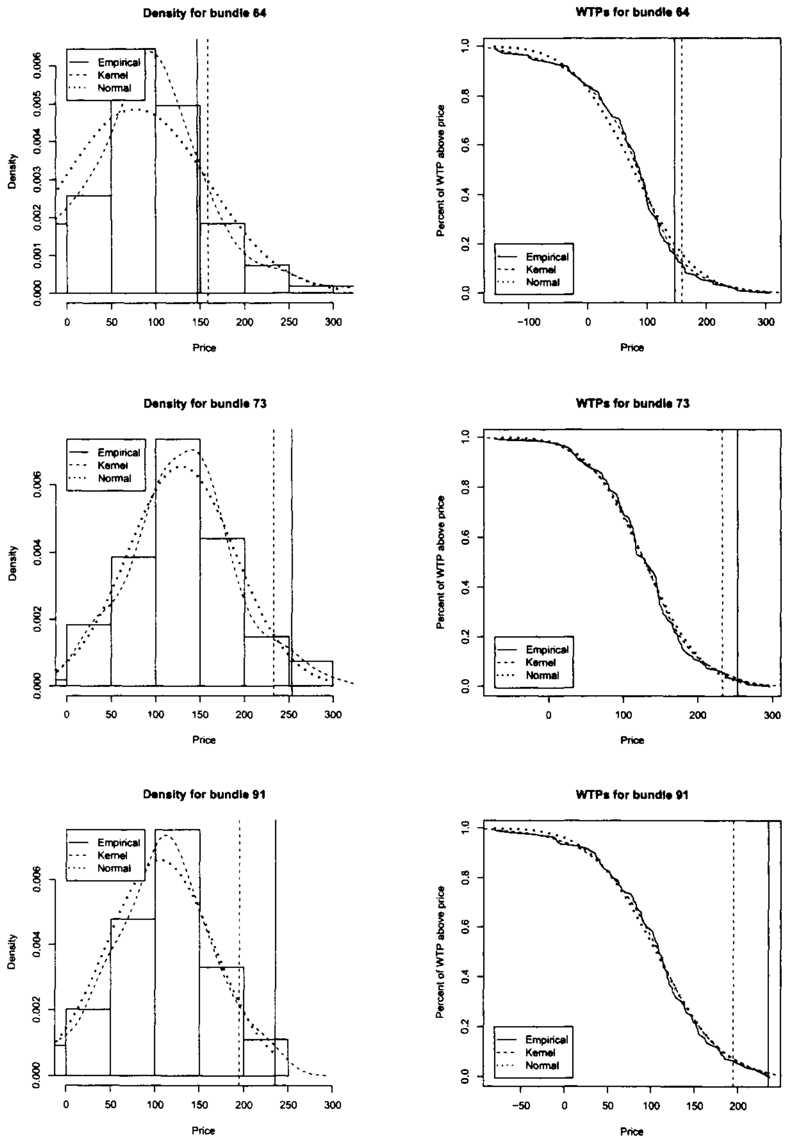


Figure 8.6: Density functions and 1-cumulated distribution functions of WTPs for bundles 64, 73, and 91.

by $\vec{p} = (p_1; \ \ldots; \ p_B)^T$. The norm for the individual's choice vector $\vec{\gamma}$ is defined as $||\vec{\gamma}|| = \sqrt{\gamma_1^2 + \ldots + \gamma_B^2}$.

To maximize his or her surplus by selecting zero or one of the offered bundles each consumer i is faced with the following maximization problem for the surplus function:

$$\max \quad \vec{\gamma_i}^T \cdot (\vec{WTP_i} - \vec{p}) \tag{8.1}$$

subject to

$$\vec{\gamma} \in \{0,1\}^B \tag{8.2}$$
$$||\gamma|| \leq 1. \tag{8.3}$$

The maximization problem in Equation (8.1) fully describes the choice behavior for each consumer i confronted with different bundles j each offered at a price p_j. The condition that the individual chooses a bundle only if his or her willingness-to-pay is greater than the sales price is ensured by (8.1). The constraint (8.3) ensures that the individual can choose at most one product bundle.

Since the vendor of the bundles can assign different prices, we define a choice function f for each individual which takes the current prices as an argument:

$$f_i(\vec{p}) = \arg\max_{\vec{\gamma_i}} \quad \vec{\gamma_i}^T \cdot (\vec{WTP_i} - \vec{p}). \tag{8.4}$$

This functions has the same constraints as the maximization problem above and returns the choice behavior $\vec{\gamma_i}$ for each individual i that is offered different bundles at prices $\vec{p}$.

With the choice behavior γ_i known for each consumer facing the choice between the bundles in the bundle space B, the vendor can find the optimal pricing strategy for the offered bundles. In view of the cost structure for the bundles denoted by vector $\vec{c}$ this is done by maximizing the following profit function:

$$\arg\max_{\vec{p}} \quad \sum_{i=1}^{N} (f_i(\vec{p}))^T \cdot (\vec{p} - \vec{c}) \tag{8.5}$$

subject to

$$\vec{p} \in \mathbb{R}^{+B}. \tag{8.6}$$

In the following different simulation are presented in which one or many bundles are offered. In the cases when only single bundles are offered the bundle space B simply consist of one bundle only. The consumer's choice behavior and the maximization problems are the same for one and many bundles.

Rank	Bundle	Opt. Price	Max. Profit	Units	Share of Customers
1	26	244,-€	1108,80 €	16	15 %
2	31	218,-€	630,40 €	16	15 %
3	64	159,-€	620,20 €	14	13 %
4	73	233,-€	415,80 €	7	6 %
5	49	195,-€	390,40 €	16	15 %
6	91	210,-€	222,00 €	5	5 %

Table 8.4: Optimal prices and profits under pure bundling for bundles 26, 31, 49, 64, 73, and 91.

8.4.2 One Bundle Under Pure Bundling

The first simulations presented are for the choice of different bundles each offered separately under pure bundling. The bundles used in the simulations are 26, 31, 49, 64, 73, and 91. Each simulation was performed separately for the different bundles. At every given price the share of customers who would buy the bundle is found by counting how many customers have a willingness-to-pay which is higher than the sales price. This is equal to empirically solving maximization problem 8.1 for each customer. Simulation for positive prices and calculating the resulting profits the highest possible profit can be found. This is equal to empirically solving maximization problem 8.5.

In Figure 8.7 the profits for each bundle offered alone under pure bundling for the 109 customers in the dataset is shown. The solid line denotes the profit at different prices. The optimal price is denoted by the vertical dashed line, the list price by the vertical solid line.

The results for the simulations with the six bundles are given in Table 8.4. Bundle 26 yields the highest profit, followed by bundles 31, 64, 73, 49, and 91. If the retailer was to offer the telephone 6230 with "D1-Relax 100" contract under a pure bundling strategy and had the choice between the discussed bundles, number 26 should be offered for sale at a price of 244,- €. At this price a share of around 15% of the customers would accept the offer, and based on the 109 customers in the dataset this would yield a profit of 1108,80 €.

The retailer could also promote certain accessories. For example to promote the extra battery charger "DCV-14", bundle 64 could be offered. At the optimal price of 159,- € around 13% of the customers would accept the bundle. To attract more customers to the promotion the retailer could lower the price for bundle 64. Based on the data from the estimation procedure it is also possible to estimate the share of customers for a specific price. If the retailer wished to increase the sales to slightly above 20% of the customers, the price would have to be set at 136,- €. For the 109 individuals in the dataset this would result in a profit of 489,90 €.

Note that the knowledge of the share of customers who accept a product offering at a given price as well as the knowledge of customers who are not willing to pay the given price permits the estimation of market expansion and contraction. By lowering the price from 159,- € to 136,- € for bundle 64 the market is expanded by 9 customers. This is

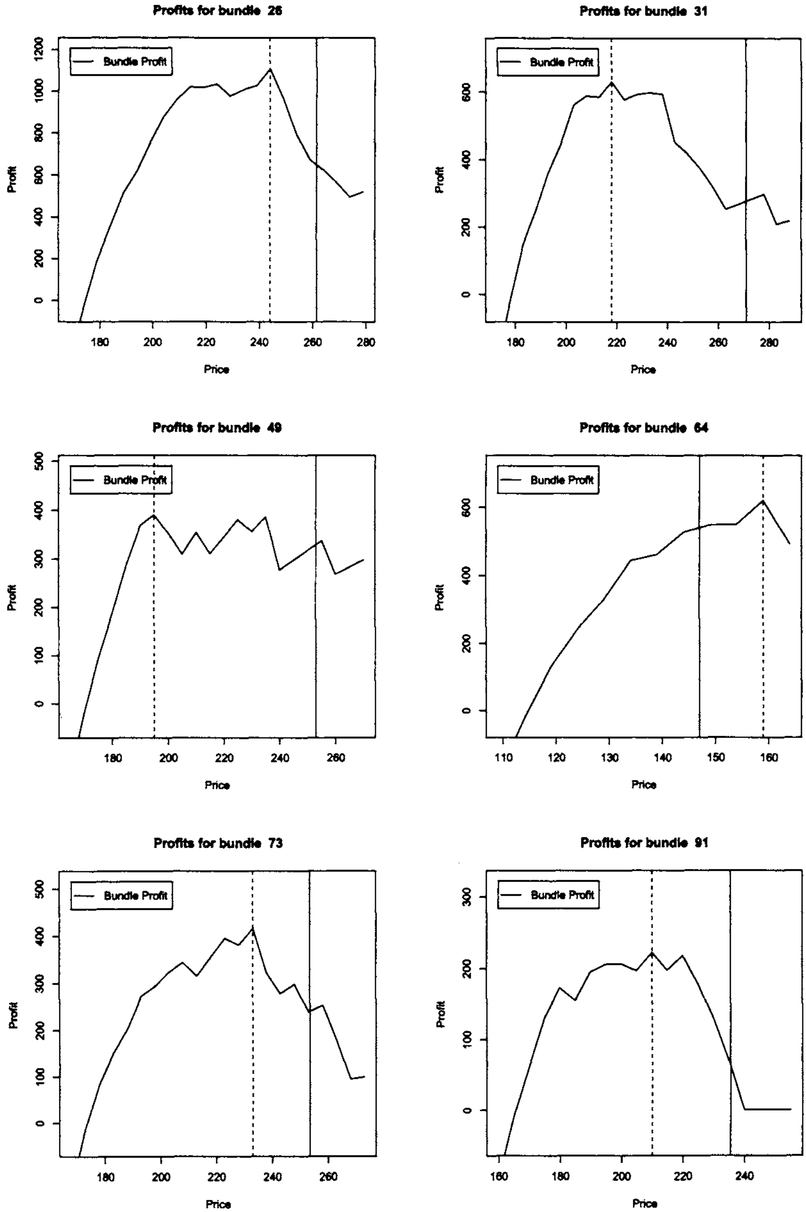


Figure 8.7: Profits under pure bundling for bundles 26, 31, 49, 64, 73, and 91.

Rank	Bundles	Max. Profit	Opt. Prices	Units	Share
1	26, 64	1501,80 €	244,-€, 159,-€	14, 12	24 %
2	26, 31	1326,60 €	244,-€, 238,-€	14, 6	19 %
3	26, 49	1222,90 €	244,-€, 235,-€	13, 5	17 %
4	64, 73	877,80 €	159,-€, 238,-€	14, 4	17 %
5	31, 49	700,40 €	218,-€, 245,-€	14, 2	15 %
6	73, 91	430,20 €	233,-€, 210,-€	5, 3	7 %

Table 8.5: Simultaneous offering of two Bundles

an expansion of 69%.

8.4.3 *N* Bundles Under Pure Bundling

At the Nokia online shop different bundles are offered. The dataset can also be used to simulate choice behavior for competing bundles that are offered simultaneously. Here we will show how customers behave when two bundles are offered at the same time. Without loss of generalization simulations for only two bundles are used. The reason is that results for two competing bundles can be presented graphically which is not possible for more bundles.

The choice behavior of the consumers who can choose only one of the offered bundles is also described by the maximization problem 8.1. Unlike the previous section the bundle space now contains two bundles. The optimal pricing for the two bundles is again found by empirically solving maximization problem 8.5.

The results for 6 different combinations of two bundles are shown in Figure 8.8. In each case two bundles are offered simultaneously, and the profit at each price level is calculated based on the choices of the respondents. The highest possible profit is marked by an arrow.

The resulting optimal prices and profits from the simulation are shown in Table 8.5. The most profitable bundle combination of two bundles is 26 and 64 yielding a profit of 1501,80 € selling to a share of 24% of the customers. The possible profit derived from offering two bundles simultaneously is higher than offering one. This can be seen by comparing the possible profits from offering one bundle only shown in Table 8.4. Compared to the highest possible profit of 1108,8 € from offering bundle 26 alone, the profit can be increased by 26% (calculated by $(1501,80$ € $- 1108,80$ €$)$ / $1501,80$ € $\approx$ 26%), when bundle 26 and 64 are offered simultaneously.

However, when more bundles are offered at the same time they might cannibalize one another. As shown in the last section, when bundle 26 is offered alone at the optimal price of 244,- €, 16 units of the bundle are requested by the customers. When bundle 26 and 64 are offered simultaneously, the optimal price for bundle 26 remains unchanged. Nevertheless, 2 customers have switched to buying bundle 64 as can be seen in Table 8.5. Now only 14 units of bundle 26 are requested. The cannibalization between the two bundles is even stronger when bundle 26 is offered together with bundle 49. With the optimal price for bundle 26 unchanged 3 customers switch to bundle 49.

Besides the switching between the two bundles, market expansion occurs when bundles 26 and 64 are offered simultaneously. Compared to offering only bundle 26 at 244,- €, when 16 customers were served, the market has been expanded by 10 individuals. This is a market expansion of 63% (calculated by $(26 - 16)/16 \approx 63\%$).

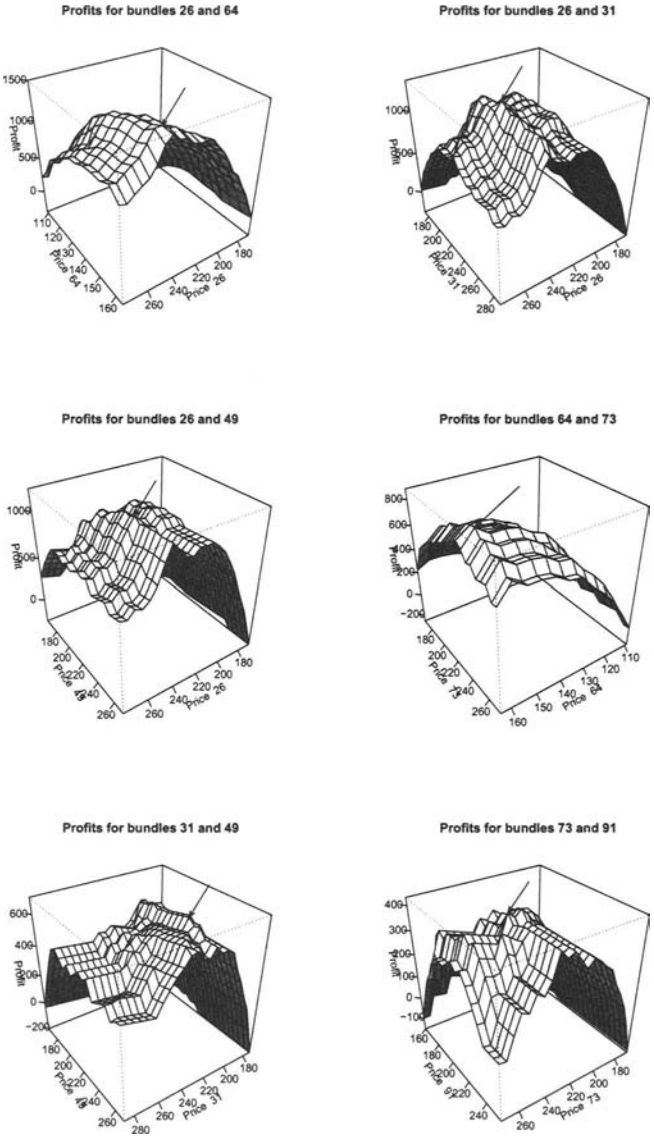


Figure 8.8: Results for the simultaneous offering of two bundles. The maximum profit is marked by an arrow.

8.4.4 One Bundle Under Mixed Bundling

Looking at Figures 8.5 and 8.6 which show the density of the consumers' WTPs for the bundles 26, 31, 49, 64, 73, and 91, it can be seen that there is always a share of customers who would be willing to purchase the bundles at list price. The dataset used for the simulations contains individual level WTPs for all possible product bundles. Therefore, when all bundles are offered simultaneously at the regular list price a mixed bundling strategy can be simulated. Under mixed bundling all possible products are additionally offered for regular sales at list price. When all possible bundles are offered any combination of single products is offered.

In this simulation each customer can choose the offered product bundle at discounted price or any other product combination consisting of telephone, contract and accessories at list price. Note that the dataset also contains the empty bundle, which consists of only telephone and contract.

Consumer choice under mixed bundling is also describe by the maximization problem in Equation (8.1). In this case the bundle space contains all possible product bundles, of which one has a discounted price. Each customer can choose one product bundle. As in the previous sections, the optimal pricing for the offered product bundles is found by empirically solving maximization problem 8.5.

The offering of product bundles at discounted price in the presence of regular sales mimics the purchase situation in the online shop of Nokia more closely than the simulations for pure bundling strategies. In the online shop the full product range is always offered at list price and no exclusive items exist that are only sold in special offerings.

A retailer who offers a product bundle at discounted price that competes with regular sales faces three situations:

1. Individuals that would buy some other bundle at list price switch to the bundle offered at discounted price.

2. Individuals that would not buy anything at list price buy the bundle offered at discounted price.

3. Individuals that are willing to buy the discounted bundle at list price pay only the discounted price.

In the first situation the retailer can increases or decrease profit. Profit can be increased if the bundle at discounted price has a higher margin than the bundle the customers would otherwise buy at the list price. Profit is decreased, if the bundle offered at a discount yields a lower profit than the offerings the individuals would otherwise buy. Either way this is a cannibalization effect. Whether cannibalization increases or decreases profit depends on the WTPs in the customer population and the cost structure of the different bundles. To distinguish whether cannibalization leads to a higher or lower profit we refer to the effect as *positive-* or *negative cannibalization.*

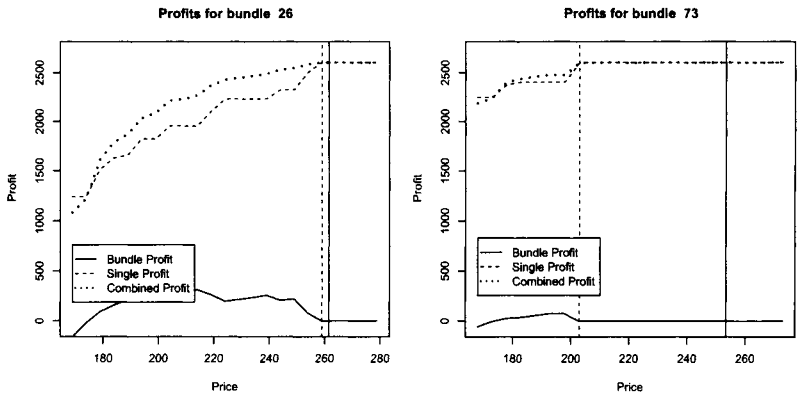


Figure 8.9: Offering of bundles 26 and 73 in the presence of regular sales.

In the second situation the profits are always increased because new customers enter the market. This effect is called market expansion.

In the third situation profits are always decreased because the customers buy the product bundle at a discounted price, even though they are willing to pay the list price. Therefore, the sales at list price are cannibalized by the sales at discounted price, and a negative cannibalization effect occurs.

In Figures 8.9 to 8.11 the results of simulations for the different product bundles in the presence of regular sales are shown. The solid line in each figure denotes the profit realized from the sales of the corresponding bundle at discounted price. The dashed line is the profit from regular sales, and the dotted line is the sum of the two profit lines. The solid vertical line denotes the list price for the corresponding product bundle and the dashed vertical line denotes the optimal price.

Figure 8.9 shows that the highest profit for bundles 26 and 73 is realized when the optimal prices of the bundles denoted by the vertical dashed lines are set so high that no customer would accept the offer. This can also be seen from the dotted profit line which never raises above the dashed profit line, meaning that the combined offering of a bundle at any price in the presence of regular sales can never outperform regular sales alone. If the price for either bundle is set such that some customers prefer to buy the bundle over the best alternative at list price, the overall profit is lowered. Therefore, discounting bundles 26 and 73 is not profitable for the retailer.

For bundles 31, 49, 64, and 91 the situation is different. As can be seen in Figures 8.10 and 8.11, introducing these bundles the retailer can increase profit, compared to the profits from sales at list price. The combined profit denoted by the dotted line has a maximum above the highest profit from sales at list price denoted by the dashed line.

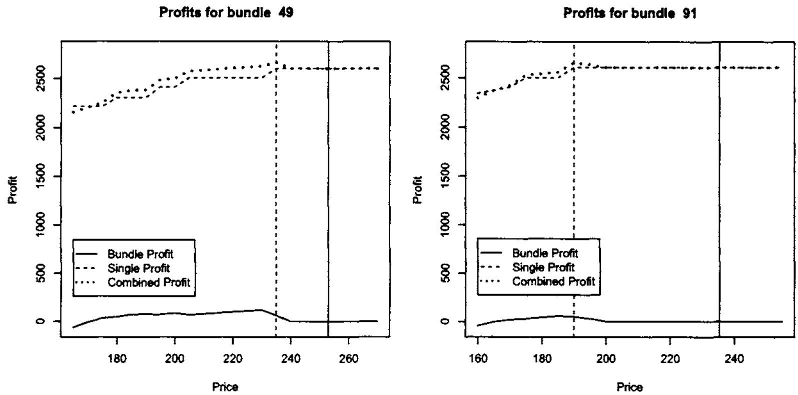


Figure 8.10: Offering of bundles 49 and 91 in the presence of regular sales.

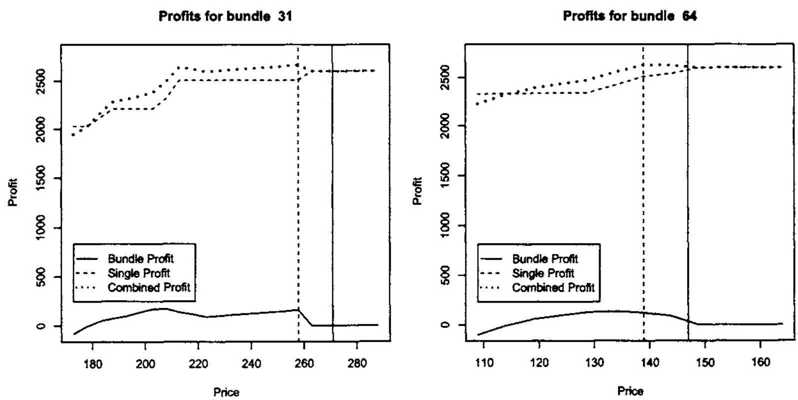


Figure 8.11: Offering of bundles 31 and 64 in the presence of regular sales.

Rank	Bundle	Max. Profit	Opt. Price	Units R. Sales	Units Bundle	Max Profit R. Sales
1	49	2670,35 €	235,- €	50	1	2605,95 €
2	31	2669,90 €	258,- €	49	2	2605,95 €
3	91	2654,75 €	190,- €	50	2	2605,95 €
4	64	2633,20 €	139,- €	47	5	2605,95 €
5	73	2605,95 €	203,- €	50	0	2605,95 €
6	26	2605,95 €	259,- €	50	0	2605,95 €

Table 8.6: Offering of different bundles in the presence of regular sales.

The optimal prices and corresponding profits are summarized in Table 8.6. The most profitable bundle is number 49 which can increase profit by 2% compared to the sales from list price alone (calculated by (2670,35 € – 2605,95 €) / 2605,95 € ≈ 2%). Next best bundles are 31 and 91, also with a 2% profit increase, followed by bundle 64, which has a 1% profit increase.

Table 8.6 also shows market expansion and switching effects. At list price 50 out of 109 customers would buy a product bundle. When bundle 49 is offered at the optimal price, the market is expanded by one individual who would not buy anything at list price. This can be seen in the units of the list price which remain at 50. The same happens for bundle 91. For this bundle the market is expanded by two customers.

If the prices for either one of bundle 49 and 91 were gradually lowered, customers would start switching away from the alternative offerings for which they were willing to pay the list price. The cost structure of bundles 49 and 91 is such that switching to the discounted bundle would produce negative cannibalization.

Apart from market expansion cannibalization effects occur when bundles 31 and 64 are offered at the optimal prices. As can be seen in Table 8.6, at the optimal prices for bundle 31 the market is expanded by one individual, for bundle 64 by two individuals. In addition to the market expansion, some customers have switched away from their best offering at list price to buying the bundle. One individual has switched to buying bundle 31 and three individuals have switched to buying bundle 64.

The profit is increased for the bundles 31, 49, 64, and 91 even in the presence of customers switching to the discounted bundles. The reason is that either positive cannibalization occurred, or negative cannibalization is outweighed by the additional profits from market expansion.

The difference between bundles 49 and 91, for which only market expansion occurred, and bundles 31 and 64, for which additionally cannibalization effects occurred, can also be seen by comparing Figures 8.10 and 8.11. For bundles 31 and 64 shown in Figure 8.11 the profit from regular sales denoted by the dashed line dips under the maximum of the combined profit denoted by the dotted line. This dip is the decrease in profit in regular sales from the customers who have switched from regular sales to buying the bundle. For bundles 49 and 91 there is no cannibalization. Therefore, the profit line for regular sales remains at the highest level under the maximum of the combined profit as can be seen in

Figure 8.10.

Note that the simulation for mixed-bundling with one bundle, as presented here, is the same as for pure-bundling with N bundles, which was the case in the Section 8.4.3, where concurrent offering of N discounted bundles was simulated. In the simulation in this section $N-1$ bundles were offered without a discount and one bundle was offered with a discount. In both types of simulations N bundles were simulated, the only difference stems from the pricing of the bundles.

8.4.5 N Bundles Under Mixed Bundling

The following describes the scenario if the retailer would offer N bundles simultaneously in the presence of regular sales. This will be illustrate by showing a simulation for two bundles that are offered at the same time. As in Section 8.4.3, there is no loss of generalization and the reason why two bundles are used is that results for two competing bundles can be presented graphically which is not possible for more bundles.

As in the previous simulations every individual i chooses the alternative that leaves the highest surplus. This can either be one of the bundles offered at a discount or a combination of products offered at list price.

Depending on the structure of the WTPs for the different bundles and the corresponding cost structure, profits can be increased above the profit from just regular sales at list price. In Figure 8.12 the results of the simulations are shown. The first two bundle combinations, bundles 49 and 91 and bundles 31 and 91, have one optimal price combination for the two bundles. The maximum profit for each bundle combination is marked by an arrow.

Note that each of the bundles 31, 49, and 91 can also increases profit when they are offered as a single bundle under a mixed bundling strategy. This was shown in the previous section. It is obvious that offering any combination of bundles that would increase profit if each of them was offered alone will also increase profit if they are offered simultaneously.

In the third bundle combination consisting of bundles 39 and 49 in Figure 8.12 two bundles are offered that would each increase profit if they were offered alone under mixed bundling. However, if they are offered together it is optimal to price bundle 31 such that nobody would buy that bundle. The optimal profit for this bundle combination is at the optimal price of bundle 49 and any price of 31 which nobody would accept. Because there exist many optima, each one is denoted by a dot, and the dots form a line along the optimal price for bundle 49.

In the fourth and the fifth bundle combinations in Figure 8.12 two are offered, of which only one can increase profit when offered alone under mixed-bundling. The profitable bundles are 31 and 91, additional profit from offering bundle 73 cannot be gained. When both bundles are offered simultaneously, it is optimal to offer bundle 73 at a price at which nobody would accept the bundle. For the profitable bundle it is optimal to set the same price as if the bundle was offered alone. Therefore, the outcome is the same as in the previous section, when the bundles 31 and 91 were offered alone. The optimal prices are again marked by several dots along the optimal prices for the profitable bundle.

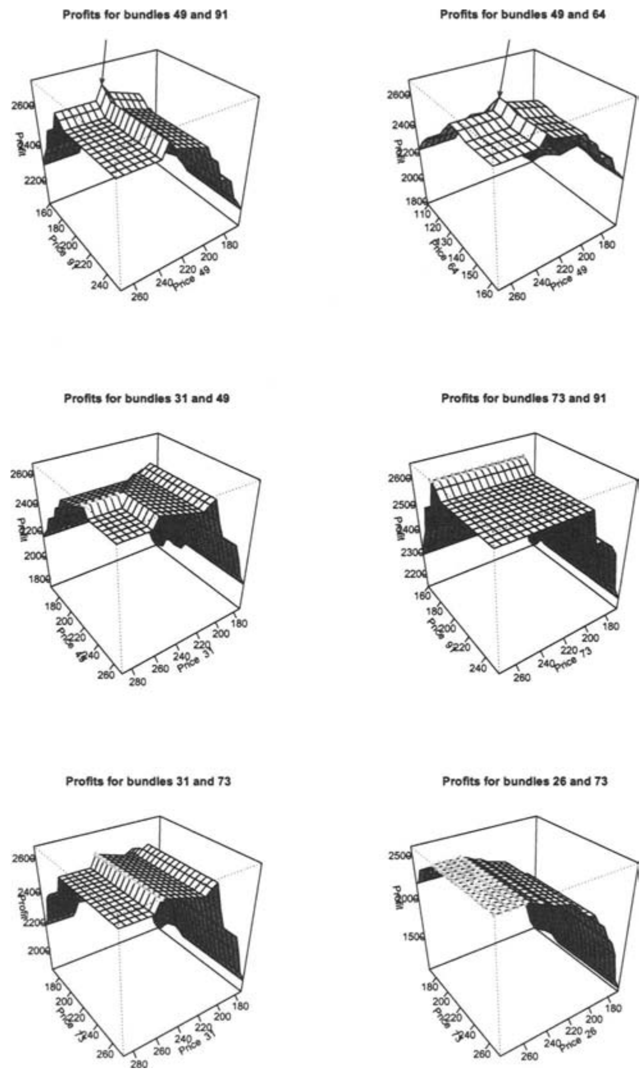


Figure 8.12: Offering of two bundles in the presence of regular sales.

Rank	Bundles	Max Profit	Opt. Prices	Max Profit R. Sales	Units	Units R. Sales
1	49, 91	2719,15 €	235,-€, 190,-€	2605,95 €	1, 2	50
2	49, 64	2697,60 €	235,-€, 139,-€	2605,95 €	1, 5	47
3	31, 49	2670,35 €	263,-€, 235,-€	2605,95 €	0, 1	50
4	31, 73	2669,90 €	258,-€, 203,-€	2605,95 €	2, 0	49
5	73, 91	2654,75 €	203,-€, 190,-€	2605,95 €	0, 2	50
6	26, 73	2605,95 €	259,-€, 203,-€	2605,95 €	0, 0	50

Table 8.7: Offering two bundles in the presence of regular sales.

For the last bundle combination consisting of 26 and 73 in Figure 8.12 profits cannot be increased above profits from regular sales. Therefore, it is optimal to set the prices for the two bundles such that nobody would buy the bundles. There exist different price combinations such that nobody would choose any of the two bundles. Each one is marked by a dot, and the dots form a squared surface area.

The results of our simulation are summarized in Table 8.7. The most profitable bundle combination is 49 and 91. Compared to regular sales the profit is increased by 4% compared to regular sales alone (calculated by $(2719,15\ € - 2605,95\ €)\ /\ 2605,95\ € \approx 4\%)$. The next best combinations are bundles 49 and 64, with a profit increase of 3%, followed by bundles 49 and 64 and bundles 67 and 91, each with a profit increase of 2%. From offering the two bundles 67 and 73 simultaneously under mixed bundling no additional profit can be gained.

However, two profitable bundles offered simultaneously might cannibalize one another. In this case it is possible that the profit from offering the better bundle is lowered upon introduction of another bundle. Nevertheless, the profit cannot be decreased below the profit from offering the second-best bundle alone.

For the simultaneous offering of 49, 91 the two bundles do not cannibalize one another. The optimal prices for the two bundles and the units of the bundles sold are the same, as when they were offered alone under mixed-bundling. Comparing the units and prices of the two bundles in Table 8.7 with the units in Table 8.6 in the last section, this can be seen.

Bundles 49 and 91 also do not cannibalize sales at list price, because the units sold at list price remain at 50, which is the highest possible number of units. When the two bundles are offered at the optimal prices, the market is expanded by three individuals. The profit which can be reached by offering the two bundles simultaneously is the sum of the excess profit when offered separately.

This is different for bundles 49 and 64. These bundles cannibalize the sales of product combinations at list price. This can be seen in Table 8.7 as the regular sales have decreased by three individuals to 47 units. Three individuals have switched from buying a product combination at list price to one of the offered product bundles. The market has further been expanded by 3 individuals.

The pricing strategy for the two bundles 49, 91 and 49, 64 is the same as if they were offered separately. Since only the profitable bundle is offered at an acceptable price, the profit increase is due to that bundle. The increase in profit is therefore the same as if the profitable bundle was offered alone.

The last row in Table 8.7 shows the unprofitable bundles 67 and 73. Of each bundle 0 units are sold, and the profit solely stems from regular sales.

8.5 Summary

In this chapter the results of our empirical investigation were presented. A web-based conjoint interview was performed to which the PE scene was appended. In this investigation WTPs for different product bundles were estimated at the individual level.

In the first two sections the design of our conjoint studies was discussed and the probands' response behavior to the online survey was presented. The response rates and the behavior of the participants is similar to other online surveys published in different articles.

In the third section the respondents' WTPs for one product bundle were graphically presented. The often found assumption that consumers willingness-to-pay is normally distributed was also discussed. Our data indicates that this assumption cannot be rejected.

In the fourth section it was shown how price response behavior under different bundling strategies can be simulated. Based upon the individual level WTPs, estimated by the PE scene, price response behavior for the different bundling strategies pure-bundling, and mixed-bundling was simulated. For mixed-bundling any product combination which is purchased at list price was considered to be the unbundled sales. A pure-unbundling strategy was implicitly simulated in the cases of mixed-bundling in which a bundle was offered but not chosen by any individual of the dataset.

For pure-bundling and mixed-bundling the offering of one and many bundles at a discounted price was simulated. For each simulation an optimal pricing strategy was found which leads to the maximum profit. Further, the sales volumes, market expansion effects, and cannibalization were simulated.

However, the optimal pricing strategies could also have been obtained by simulations based on data elicited by discrete choice analysis. The benefit of the PE scene is that it provides individual level WTPs. Therefore not only optimal pricing strategies can be found, but also cannibalization effects can be simulated. Since discrete choice analysis only provides aggregate level estimations, individual level switching behavior cannot be analyzed.

Chapter 9

Summary and Main Findings

9.1 Summary

This dissertation proposed and tested a new method to estimate willingness-to-pay (WTP). For practical applications the estimation of willingness-to-pay belongs to the field of strategic marketing planning. Recent developments in marketing show that pricing of products is driven by a value based approach. In a value based approache the price of a product is based on the perceived valuation of the target customers. The research in the field of pricing is of ample importance. The reason is that price is the only element of the marketing mix that generates income. All other elements, such as advertising and promotion, product development, selling effort, distribution, packaging and so forth, involve expenditures (cf. Nagle and Holden (2002, chapter 1) and Monroe (2003, chapter 1)). In order to set a good price a marketer has to anticipate the market's price response behavior. That is, the marketer needs valid estimations of the consumers' willingness-to-pay.

To describe willingness-to-pay we discussed different concepts, by which consumers' reactions to price are determined. There exist two concepts which are sometimes used synonymously in marketing literature. These are the *maximum price* and the *reservation price*. However, both concepts subsume under the more general term willingness-to-pay.

The underlying cognitive processes for the formation of the maximum price and the reservation price are different. The maximum price a consumer has for some product is formed based on some reference product, which is perceived as the best alternative, plus a differentiation value, which reflects the additional valuation for the difference between the product and the next best alternative. In contrast, the reservation price does not depend on an alternative offering. It is simply the price at which the consumer is indifferent between consuming the product or not consuming the product at all.

We have argued that for the two valuation concepts always the lower one determines the purchase decision of a consumer. Therefore, when a consumer's willingness-to-pay is estimated, the researcher never knows whether the maximum price or the reservation price determines the estimation.

However, this is not so critical after all. We have shown that the valuation mechanisms maximum price and reservation price for different product alternatives have a linear relationship with the products' utility. Furthermore, the two relationships are also parallel. Because of the linearity and the parallelism a marketer need not know, which concept determines willingness-to-pay, as long as a customer's choice behavior can correctly be predicted. Therefore, the more general term willingness-to-pay under which the two concepts maximum price and reservation price subsume can be used.

With the concepts maximum price and reservation price discussed and the subsuming term willingness-to-pay established, different measurement techniques that are applied in marketing applications were presented. Out of the variety of instruments used in marketing, due to monetary or time constraints in the practical application surveying techniques are the preferred choice.

The estimation procedure, that was proposed in this thesis, is a surveying instrument which is based on conjoint analysis. Because of the connection between our new procedure and conjoint analysis, the latter is discussed in detail.

Conjoint analysis has a long tradition in pricing studies and especially for the estimation of willingness-to-pay. A selection of publications was presented to illustrate the developments in this research area until today. The general approach with conjoint analysis in pricing studies is to incorporate price as an attribute and estimate part-worth utilities for different price levels. Based on these estimations a linear function is fitted that maps conjoint utilities on a price scale (cf. Green and Srinivasan (1978), Pinell (1994), and Orme (2001, 2002)).

Several problems can be identified that arise in traditional pricing studies by conjoint analysis:

1. *Theoretical Problems*: By treating price as an attribute in a conjoint study part-worth utilities are estimated for the presented price levels. By economic definition price does not have a utility, rather it reflects the foregone alternative consumption (with the associated utility) if a product is purchased.

2. *Practical Problems*: The inclusion of price leads to several unwanted effects such as the *price effect*, the *range effect*, and the *number of levels effect*. These effects occur when the number of levels of an attribute is changed in a conjoint study. However, price does not have a natural number of levels. Therefore, the attribute price can often not be configured as would be best for the objective of the pricing study.

3. *Estimation Problems*: Traditional conjoint analysis does not incorporate a decision rule. This makes the estimation of choice behavior difficult. To estimate willingness-to-pay choice information is needed. This information is usually added to the data by assuming or explicitly asking the respondents for a status quo product, that the respondent would actually purchase. In view of this status quo product all other products of the study are priced. However, a priori assuming a status quo product can be a great source of error. Asking each respondent for only one status quo product might not bear sufficient information to estimate willingness-to-pay for all possible product realizations.

Our new estimation procedure overcomes these problems by not including price in the conjoint analysis, but rather estimating the linear relationship between conjoint utilities and willingness-to-pay in an additional interview scene. We call the new scene Price Estimation scene (PE scene). The PE scene is as a choice scene subsequent to a conjoint analysis.

The PE scene was tested in an empirical investigation on willingness-to-pay for product bundles in the Nokia online shop. Before the investigation the shop already offered product bundles. However, the prices of the product bundles were set based upon the cost structure of the products and expert knowledge of the target market.

Simulations were performed for different types of bundling strategies. These were *pure-bundling* and *mixed-bundling*. Simulations are a powerful instrument to design pricing strategies, in this case, for product bundles. We were able to (1) identify product bundles that yield profit increases compared to regular sales only and (2) to find optimal pricing strategies for the identified bundles.

Apart from designing novel pricing strategies for new and existing products (or product bundles), the PE scene can also be used to evaluate current pricing strategies to identify unexploited profit potentials. Perhaps even more important, the procedure can be used to select a promising pricing strategy out of many possible strategy candidates.

9.2 Empirical Results

The PE scene is based on conjoint analysis. Conjoint analysis is the preferred choice when individual level preference structure is estimated based only on data provided by each respondent. Individual level estimation techniques are especially important when the preference structures of the individuals in the target is heterogeneous or a marketer cannot forecast the degree of heterogeneity of the market.

In the PE scene the respondents are presented a sequence of product choices with assigned prices and indicate whether they would actually purchase the presented product profiles. Product stimuli as well as price scales that are adapted for each proband to reflect individual choice behavior are used. Because the choices are different for every respondent the PE scene is realized as a computer based adaptive interview. To the best of our knowledge there is no other surveying method that dynamically assigns prices to product offerings.

With the sequence of screens in the PE scene we iteratively search for $\langle$*utility, price*$\rangle$-points in the *utility* $\times$ *price* space. Each point represents a respondent's willingness-to-pay at a certain utility level. Once a sufficient number of points is found and the accuracy of the search procedure is narrowed to a predefined threshold, a linear function is fitted, that represents the relationship between utility and price. With this function the willingness-to-pay for all product realizations that can be formed by the attributes and levels of the conjoint analysis can be estimated.

An empirical investigation was carried out estimating the willingness-to-pay for product bundles at the online shop of Nokia in Germany. The empirical investigation in this thesis implemented the PE scene in the modular framework of the Java Adaptive Conjoint tool (jAC version 1.1, Schmidt-Thieme (2004)), which is a re-implementation of adaptive conjoint analysis written in Java^{TM}.

A random sample of 1000 customers of the Nokia online shop was drawn, and the individuals were invited via e-mail to participate in an online survey. The response rate for the interview was 33%. The number of completed interview was 25%, and after dismissing some interviews due to unreasonable response behavior resulted in 19% valid interviews.

Respondent's reactions to the PE scene: The participants response behavior shows that from a respondent's point of view the PE scene is well suited to estimate willingness-to-pay. The response rates as well as the rates of the completed and valid interviews are high for online surveys (cf. Cobanoglu et al. (2001) and Kaplowitz et al. (2004)). Apparently, since the number of aborted interviews is relatively low, the search procedure described above converges quickly enough to yield a low abortion rate.

The bundles in the empirical investigation consist of a mobile phone with a contract bundled together with suitable telephone accessories. The conjoint analysis had the accessories to be bundled as attributes and the different types of each accessory were the levels. All attributes in the conjoint design had a "none" level configured, to represent the absence of the attribute.

With the resulting estimations of willingness-to-pay for the configured bundles the customers' response behavior was simulated for different bundling strategies.

Face Validity of Estimations: All tested bundles had an unimodal empirical distribution of the WTPs. The estimations for the respondents' WTPs yield a high face validity, because there were almost no estimations for product bundles much above the list price for the bundles.[1] From the setup of the survey this would be unreasonable behavior, because no respondent should indicate that he or she would accept a product offering at a higher price than buying the bundle components at the regular price in the online shop.

Normal distribution of WTPs: The density and distribution plots for the respondents' WTPs seem to be more or less close to a normal distribution. In the literature willingness-to-pay is often assumed to be normally distributed across consumer populations (e.g., Schmalensee (1984), Fürderer et al. (1999), and Olderog and Skiera (2000)). Based upon a Kolmogorov-Smirnov normality test the null hypothesis that the WTPs were normally distributed could not be rejected for almost all bundles at a p-value of 0.01. This means, that the cumulated empirical distribution functions does not differ highly significantly from a normal distribution for almost all bundles. At a p-value of 0.05 the null hypothesis could not be rejected for 2/3 of all bundles.

The dataset used for the simulations consisted of 109 valid interviews for one bundle type. A bundle type consists of a telephone with contract and any possible combination

[1] Face validity is an intuitive test of whether a measurement seems to measure what it is suppose to measure (cf. Anastasi (1988, p. 144)).

of telephone accessories. For every individual the dataset contained estimations for the willingness-to-pay for 108 bundle combinations. With this dataset profits and market shares for four different bundling strategies were simulated.

Single bundles under pure-bundling: With these simulations we were able to show which bundles produce the highest profit and could simulate market shares for different bundles at different prices. Simulations for 6 bundles were presented. The most profitable bundle had a maximum profit of 1108,80 € based on the data of the 109 individuals. This is a 76% higher profit than for the second best bundle, that yields a maximum profit of 630,40 €. Both bundles have a market share of 15% each. The other bundles had lower maximum profits and different market shares.

***N* bundles under pure-bundling:** With more than one bundle offered, cannibalization effects between the bundles occur. Depending on the cost structure of the bundles this can increase or decrease profits compared to offering either bundle alone. Results for 6 different combinations of 2 bundles were presented. The most profitable combination yields a maximum profit of 1501,80 € and a market share of 23%. This is a 13% higher profit than the second best combinations with a maximum profit of 1326,60 € and a market share of 18%. The most profitable bundles offered as combinations were the same as the ones offered separately. The results show that profit can be gained from offering 2 bundles simultaneously compared to only offering one bundle.

Single bundles under mixed-bundling: To mimic regular sales, all 108 bundles were offered simultaneously at list price. With this regular sales are imitated, because the 108 bundles contain all possible combinations of accessories including the empty bundle, consisting of telephone and contract only. One of the bundles was offered at a discount, that is, a price below list price. The same six bundles were used as in the simulations described above. The most profitable bundle yields a maximum profit of 2670,35 €. With this strategy 50 bundles are sold at list price and 1 unit of the discounted bundle is sold serving a share of 46 % of the customers. Note that the optimal bundle to be offered at a discount is not the same as the optimal bundle to be offered under pure-bundling.

***N* bundles under mixed-bundling:** Different bundles were selected and offered with a discount in the presence of regular sales. Besides simulating profits and finding optimal pricing strategies, we were able to show cannibalization between the bundles offered at single sales and the discounted bundles as well as between the discounted bundles among each other. Results for 6 different combinations of 2 bundles were presented. The most profitable bundle combination yields a maximum profit of 2719,15 €. With this strategy 50 bundles are sold at list price and 1 and 2 units of the two discounted bundles are sold serving a share of 49% of the customers.

With respect to the practical implications for the bundles offered at the Nokia online shop, only mixed-bundling is relevant. Because the online shop is the online retailer for Nokia in Germany, naturally the full product range is offered for single sales at list price.

Our empirical results show that the PE scene can be used to simulate pricing strategies in real world scenarios. We believe that our approach is superior to other surveying techniques when it comes to the estimation of willingness-to-pay for heterogeneous markets. Compared to other estimation approaches in which the prices are a priori fixed, the PE scene dynamically adapts the price scales to reflect different levels of WTPs of the respondents. By doing this, the problem is avoided that predefined prices although they reflect the range of current market prices, might still be unacceptable for some respondents. This is an important aspect if market expansion effects are to be predicted.

9.3 Outlook and Future Research

The main advantage of the PE scene is the "on the fly" estimation of willingness-to-pay during the interview of each respondent based on elicited choice behavior. From our point of view this cannot be achieved by other conjoint approaches, because in other approaches willingness-to-pay is usually estimated in a post-processing task. This is done by relying on strong a priori hypothesis about purchase behavior or by basing the estimations on few additionally elicited data points.

Another important instrument to estimate willingness-to-pay is discrete choice analysis, sometimes referred to as choice based conjoint (CBC). However, this class of methods does not provide "on the fly" estimations, because the participant's preference structure is also estimated in a post processing task. Furthermore, discrete choice analysis estimates preference structure at the aggregate level, and therefore needs a sufficient number of participants to perform the estimations. In contrast, the PE scene does not rely on aggregate level information.

Since the PE scene is a new method, it needs to be benchmarked against existing approaches. The next step would be to perform comparable studies with conjoint analysis in combination with the PE scene and the classical approach, which is conjoint analysis with one self-stated status quo product. Furthermore, a comparable discrete choice analysis should be carried out. The results of the three approaches should be compared to analyze deviations between the methods. Willingness-to-pay estimated by the PE scene should also be compared with revealed willingness-to-pay, that is, real purchase behavior. However, the same holds for the other estimation techniques, because only little research exists on the external validity of the existing estimation instruments.

Ultimately, we hope that the ideas and motivations behind the PE scene will be picked up by other researchers and practitioners, and can become part of the marketing toolbox for the estimation of willingness-to-pay.

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