

Price Differentiation Strategies

Dissertation

Submitted to the
Faculty of Business and Economics
University of Frankfurt

by

Agnieszka Wolk

Frankfurt am Main
2007

Foreword

Especially the Internet provides a high number of services that have very high fix costs and very moderate variable costs. This applies, for example, to offers of publishing companies, e.g., the search and retrieval of scientific publications, digital music productions, platforms for the production of weblogs and for online communities like Facebook or Xing. Frequently, companies can only offer such services profitably if they use differentiated prices. Thus every customer who pays a price above the variable costs causes a positive gross margin. Yet, the high fix costs can be covered only if at least some of the customers pay prices which lie substantially above the variable costs. Besides, the application of differentiated prices is favoured by the fact that the digitalized services can be easily changed in some attributes so that those services can be better targeted towards different segments of the market. This allows for price differentiation, a strategy where companies profitably sell fairly similar products to different consumers at different prices.

The literature, especially in economics, shows that price differentiation frequently allows for substantially increasing profits. Yet, the number of studies in the marketing area is rather limited. Therefore, it is very nice that Agnieszka Wolk focuses in her dissertation on these problems and looks at different forms of the price differentiations more thoroughly. In particular, she analyses nonlinear pricing schedules. These are pricing schedules where the average per-unit price varies in a nonlinear form with the quantity being purchased. The most prominent example is a two-part tariff which consists of a (usage-independent) fixed fee and a (usage-dependent) per-unit price. Other examples are block tariffs or quantity discounts. The basic idea of nonlinear pricing schedules is to influence consumers' usage behavior in order to increase the quantity being consumed and to skim additional consumer surplus to increase profit (or welfare).

Such nonlinear pricing schedules are especially suitable for non-storable products that are not transferable from one person to another and for which the consumer would like to consume more than one unit. The possibilities to influence consumers' usage behavior with such nonlinear pricing schedules have attracted considerable interest from both, theory and practice. In practice, these nonlinear pricing schedules are traditionally applied by companies within the telecommunication and the electric power industry. Yet, more and more companies start offering nonlinear pricing schedules. Examples are companies within the transportation

industry (e.g., the German Railway with the so called "BahnCard" or car rental companies) as well as Internet Service Providers.

In theory, the determination of nonlinear pricing schedules has been especially analyzed by researchers considering welfare theoretical problems. Starting with the work by Lewis (1941) and Coase (1946), researchers such as, e.g., Oi (1971), Leland and Meyer (1976), Faulhaber and Panzar (1977), Willig (1978), Schmalensee (1981), Goldman et al. (1984), Wilson (1993), have contributed much to our understanding of the welfare implications of such nonlinear pricing schedules. Lewis (1941) was the first to show that the use of a two-part tariff instead of a single price allows to increase welfare. Oi (1971) outlined in his seminal paper how to design optimal two-part tariffs to price differentiate among heterogeneous consumers. Leland and Meyer (1976) demonstrated that a profit maximizing firm always prefers a two-part tariff over a uniform price (later on called linear tariff). Murphy (1977), Faulhaber and Panzar (1977) as well as Willig (1978) extended this analysis and showed that adding one two-part tariff to a system with n different two-part tariffs always increases profit as well as welfare as long as there is no tariff whose per-unit price equals marginal cost. Spence (1977), Goldman et al. (1984) and Wilson (1993) specified the pricing schedule as a continuous function and achieved additional powerful insights into the characteristics of the optimal pricing schedule.

Although those papers result in a number of very important characteristics of optimal nonlinear pricing schedules, this research did not focus on the empirical estimation of consumers' usage behavior. For the insights being gained by those papers, it was sufficient to assume that individual demand functions do not cross and that the heterogeneity in consumer behavior can be characterized either by a single-dimensional type parameter (see the summaries in Brown and Sibley 1986; Mitchell and Vogelsang 1991) or, in very few cases, by multi-dimensional type parameters (e.g., Maskin and Riley 1984; Wilson 1996) which follow certain distributions and describe the deviation from an "average" demand function.

However, those researchers have not focused on the empirical estimation of consumers' usage behaviour of such tariffs. That is the contribution of the dissertation of Agnieszka Wolk. She nicely outlines a very promising approach that uses an enhanced method of conjoint analysis for estimating willingness-to-pay functions and she also presents several empirical studies in which consumers deviate from the "optimal" behaviour. Hence, her dissertation substantially enhances our knowledge in the area of price differentiation, especially in the area of

nonlinear pricing. Therefore, I strongly recommend researchers and practitioners to carefully study this dissertation.

Prof. Dr. Bernd Skiera

University of Frankfurt, Germany

References

- Brown, S.J., & Sibley, D.S. (1986). *The Theory of Public Utility Pricing*. Cambridge et al.
- Coase, R.H. (1946). The Marginal Cost Controversy. *Economica*, 13(54), 168-182.
- Faulhaber, G.R., & Panzar, J.C. (1977). Optimal Two-Part Tariffs with Self-Selection. Bell Laboratories Discussion Paper, No. 74, Bell Laboratories.
- Goldman, M.B., Leland, H.E., & Sibley, D.S. (1984). Optimal Nonuniform Pricing. *Review of Economic Studies*, 51(April), 305-320.
- Leland, H., & Meyer, R. (1976). Monopoly Pricing Structures with Imperfect Discrimination. *Bell Journal of Economics*, 7(2), 449-462.
- Lewis, A. (1941). The Two-Part Tariff. *Economica*, 8(31), 249-270.
- Maskin, E., & Riley, J. (1984). Monopoly with Incomplete Information. *Rand Journal of Economics*, 15(2), 171-196.
- Mitchell, B.M., & Vogelsang, I. (1991). *Telecommunication Pricing: Theory and Practice*. Cambridge, UK.
- Murphy, M.M. (1977). Price Discrimination, Market Separation, and the Multi-Part Tariff. *Economic Inquiry*, 15(4), 587-599.
- Oi, W.Y. (1971). A Disneyland Dilemma: Two-Part Tariffs for a Mickey Mouse Monopoly. *Quarterly Journal of Economics*, 85(1), 77-96.
- Schmalensee, R. (1981). Monopolistic Two-Part Tariff Arrangements. *Bell Journal of Economics*, 12(2), 445-466.
- Spence, A.M. (1977). Nonlinear Prices and Welfare. *Journal of Public Economics*, 8(1), 1-18.
- Willig, R. (1978). Pareto-Superior Nonlinear Outlay Schedules. *Bell Journal of Economics*, 9(1), 56-69.
- Wilson, R. (1993). *Nonlinear Pricing*. New York et al.: Oxford University Press.
- Wilson, R. (1996). Nonlinear Pricing and Mechanism Design. In H.M Amman, D. Kendrick, & J. Rust (Eds.), *The Handbook of Computational Economics*. Amsterdam.

Preface

Both practitioners and academics agree about the importance of price and its direct influence on consumers' purchase decision as well as the company profit. In the reality, we rarely see a single price for a given product. One visit in a store already shows that consumers face many various prices. This strategy of differential prices allows to increase profit but also improves consumers' situation and increases welfare.

A wide range of various price differentiation mechanisms exists on the market which makes price differentiation a very interesting phenomenon. Additionally, market developments constantly allow for new price differentiation applications. In this work, I research a fascinating topic of price differentiation, its various forms and new application possibilities in changing market areas.

I wouldn't have accomplished this dissertation if it wasn't for Prof. Dr. Bernd Skiera, whom I would like to thank for his continuous support, many fruitful discussions and suggestions that helped to shape this work. I would also like to thank my colleagues and co-authors Anja Lambrecht, Sven Theysohn, Martin Spann and Christian Schlereth for their engagement and help. I find our cooperation exciting and very stimulating. Additionally, I would like to thank the Chair of Electronic Commerce and the Marketing Department of the University of Frankfurt for great cooperative atmosphere and numerous inspiring discussions. Especially, I am grateful to Prof. Dr. Daniel Klapper, who together with Prof. Dr. Bernd Skiera, reviewed this work.

Lastly, I would like to thank my mother, Feliksa Prokopowicz, and my husband, Wojciech Wolk, for their support in good and bad times.

Agnieszka Wolk

Frankfurt am Main, December 2007

Table of content

| | |
|--|-----|
| Synopsis | 1 |
| Cumulative Dissertation | |
| I. Der Paid Content-Markt – Eine Bestandsaufnahme und Analyse von Preisstrategien | 25 |
| II. Multi-Channel Pricing Strategy: To Price Differentiate or Not | 47 |
| III. Augmented Methods of Conjoint Analysis to Estimate the Willingness to Pay for Multiple-Unit Products | 71 |
| IV. The Influence of Tariff-Specific Preferences on Tariff Choice and Usage | 107 |
| V. Established Phenomenon or Occasional Incident? Persistence of Tariff-Choice Biases across Pricing Schemes | 125 |
| VI. The Effects of Reference Prices on Bidding Behavior in Interactive Pricing Mechanisms | 151 |

Synopsis

1. Introduction

Pricing has been long recognized as a crucial aspect of marketing strategy which is reflected in the amount of research devoted to pricing strategies (see for review Gijsbrechts 1993; Rao 1984; Tellis 1986). Pricing decisions have gained even more importance after the companies realized that superior pricing strategies have a significant influence on profitability (Marn et al. 2004; Simon 1992). While many dimensions and facets of pricing have been identified (Gijsbrechts 1993; Tellis 1986), price differentiation where a company charges consumers differential prices for a generally the same product (Skiera 1999) has been recognized as a profitable pricing strategy and as such attracted a lot of attention.

Researchers argue that price differentiation should be used whenever possible because it is always more profitable than uniform pricing (Philips 1989; Whinston et al. 1997). Many studies have empirically shown that when consumers' valuations differ, a firm can increase profits by charging consumers differential prices. Montgomery (1997) analyzes micro-marketing pricing strategies and finds that this form of price differentiation increases profit by 4% - 10%, while Chintagunta et al. (2003) report even higher profit increase of 10% - 16%. Further, Khan and Jain (2005) show that increase in profits due to nonlinear pricing equals to 26%, due to store-level pricing 10%, and when both are used profit increases by 34% compared to the situation when no price differentiation is used. Also, Leslie (2004) who analyses various forms of price differentiation (i.e., couponing and quality based) shows profit increase of 5% - 7% under price differentiation relative to uniform pricings. Consequently, many retailers engage in some form of price differentiation in order to increase their profits (Khan and Jain 2005).

Various possibilities for price differentiation emerge depending on the extent of a company intervention. Based on this criterion Skiera (1999) distinguishes between two types of price differentiation: (1) price differentiation with no self-selection where a company separates consumers into segments that are charged different prices for a given product and (2) price differentiation with self-selection where a company offers different versions of generally the same product at different prices and allows consumers to choose the most preferred alternative. Within these two general possibilities for price differentiation a large variety of applications exists which are briefly described below.

In case of price differentiation with no self-selection the company decides upon the pricing strategy for each segment and consumers may only choose whether to accept or reject the company's offer (Moorthy 1984). This pricing strategy can be individually-oriented or group-

oriented (Skiera 1999). In case of individually-oriented price differentiation, the company sets the price for each consumer according to his willingness to pay (WTP) which allows to extract the entire consumer surplus from all consumers. This type of price differentiation corresponds to the first-degree price discrimination proposed by Pigou (1920). In case of group-oriented price differentiation with no self-selection, a firm divides the market into few segments of consumers that are similar on some characteristics but differ from other segments with regard to their demand and sells a given product to these segments at different prices based on their different price elasticities. Segmenting criteria in this case may include demographics (e.g., differentiation based on employee status in case of public transportation, cinema tickets, etc.) or location (e.g., store-level pricing or micro-marketing, Khan and Jain 2005) (Skiera 1999).

In case of self-selection price differentiation the company offers a range of product variants at differentiated prices for which consumers' willingness to pay varies and consumers are allowed to choose the product that meets their preferences. Various possibilities have been identified with regard to self-selection price differentiation depending on the dimensions on which the products differ, e.g., quantity-oriented, time-oriented, version-oriented and search-cost-oriented (Skiera 1999).

Quantity-oriented price differentiation occurs when average price per unit differs according to the quantity the customer purchases (Skiera 1999). In this case, a consumer decides upon the consumed quantity and thus self-selects the average price paid. This price differentiation corresponds to Pigou's (1920) second-degree price discrimination and is also known as nonlinear pricing. In the consumer packaged good industry it takes a form of quantity discounts where several package sizes of identical product are offered with larger packages sold at a lower per unit price (Cohen 2002; Dolan 1987; Khan and Jain 2005). In case of services, such as amusement parks or telecommunication, companies offer various tariffs such as flat-rates or two-part tariffs instead of charging a uniform price (Oi 1971). Recently, optional tariffs have become very popular and companies increasingly offer a menu of various tariffs among which consumers can choose rather than a uniform nonlinear pricing scheme (e.g., Iyengar et al. 2007; Lambrecht et al. 2007).

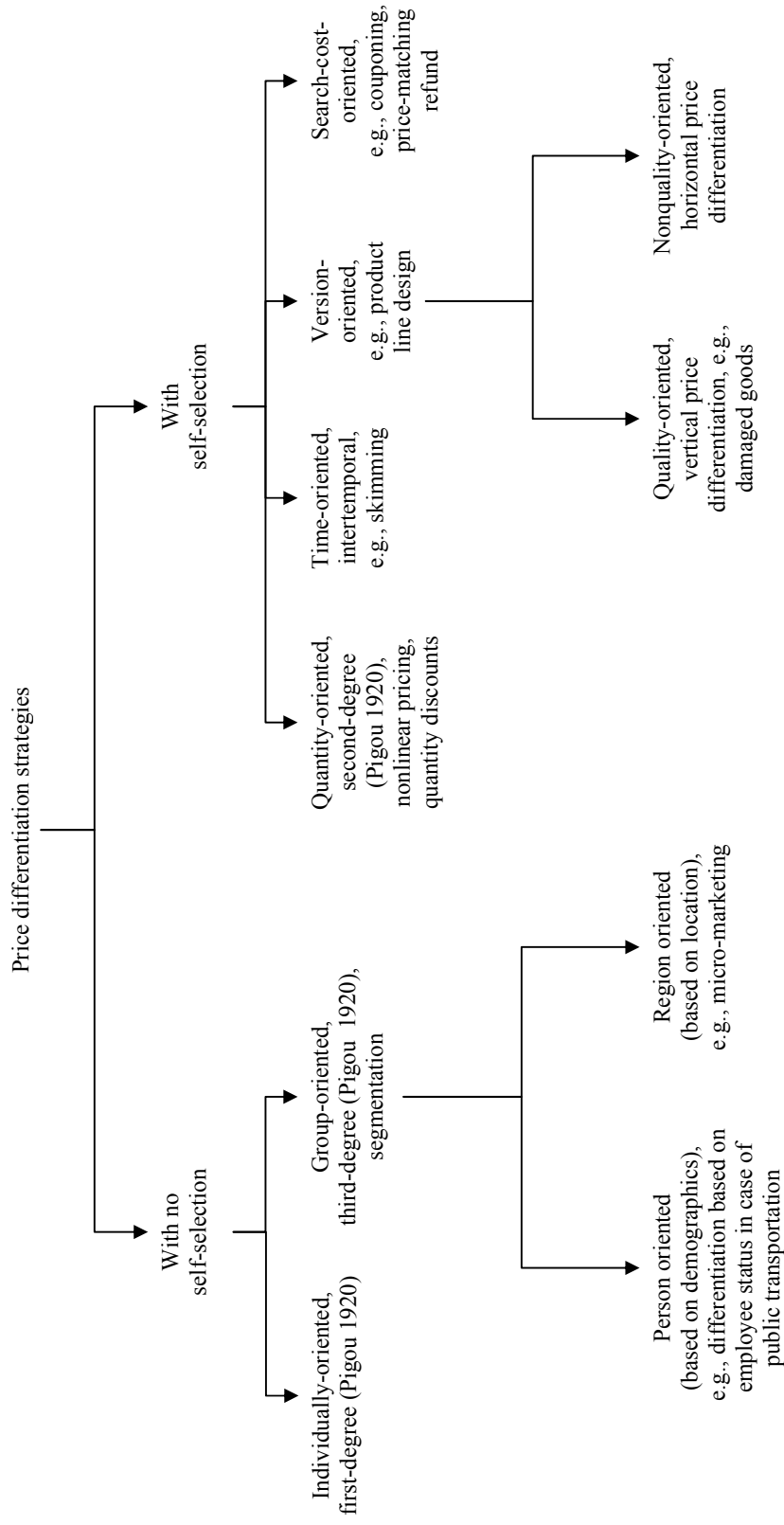
When price of the product depends on the time aspect, we talk about time-oriented (Skiera 1999) or intertemporal (Kahn 1986; Stokey 1979) price differentiation strategy. In this case a company charges customers differently depending on the time of the purchase. The examples include differentiated prices between time of the day (e.g., cheaper public transportation

tickets during the day, happy hours in restaurants), day of the week (e.g., cheaper weekends for mobile phones), and season of the year (e.g., off-season clothing and traveling). Additional forms include advanced purchase discounts when consumers buy product in advance, e.g., flight tickets (Xie and Shugan 2001) as well as skimming (penetration) strategies where a company offers higher (lower) prices after product introduction and decreases (increases) them with time (Spann et al. 2007).

Another possibility for engaging in self-selection price differentiation is to offer the same core product in a range of different versions and charge differential prices for these versions allowing consumers to self-select and purchase the version that meets their preference (i.e., versioning, Shapiro and Varian 1998). Various studies analyzed pricing of such a product line design (Dobson and Kalish 1988; Draganska and Jain 2005; Moorthy 1984; Reibstein and Gatignon 1984). When products are differentiated based on their quality and all consumers rank these versions in the same way, we talk about quality-oriented price differentiation (Skiera 1999) known also as vertical price differentiation (Bhargava and Choudhry 2001; Shaked and Sutton 1987) or damaged goods (Deneckere and McAfee 1996). When products are differentiated based on nonquality attributes (e.g., color, shape, size) and consumers rank them differently depending on their heterogeneous tastes, we talk about horizontal price differentiation (Lancaster 1990).

Lastly, companies can take advantage of the fact that consumers with higher search costs have higher willingness to pay (Tellis 1986) and engage in search-cost-oriented price differentiation where consumers with higher search costs are charged higher price. In this case, companies offer various sales promotion actions and consumers can take advantage of them depending on their willingness to engage in these actions (e.g., couponing, Anderson and Song 2004; Narasimhan 1984; or price-matching refund policies where the seller refunds the difference between his price and the lowest market price for the same products in case a buyer undertakes the effort to find one, Jain and Srivastava 2000; Png and Hirshleifer 1987). Figure 1 presents the summary of various price differentiation possibilities

Figure 1. Typology of price differentiation strategies.



Based on Skiera (1999)

Relative efficacy of each type of price differentiation mechanism depends on the kind of information necessary for its successful application as well as the company possession of this information. In case of individually-oriented price differentiation with no self-selection the company needs the information about willingness to pay for each consumer. Because this requirement is very difficult to meet, this type of price differentiation is rather a theoretical concept than a widely applied pricing strategy (Philips 1989). Lower requirements are necessary for group-oriented price differentiation where the company needs the information about consumer's segment membership and segment-specific willingness to pay. With regard to segment membership, researchers have analyzed various observable consumers' characteristics that could potentially be used for consumer segmentation. Whereas some of them have shown that these characteristics can influence price sensitivity and thus be used for segmentation (Hoch et al. 1995), most of the research shows no such a relationship (Elrod and Winer 1982; Rossi and Allenby 1992). With regard to segment-specific willingness to pay, in most cases companies are more likely to know distribution of consumer valuations in the market rather than the exact valuation of any specific consumer prior to the sale. As a result, price differentiation with no self-selection may incur many difficulties and be costly for companies. On the other hand, self-selection price differentiation poses less requirements because it does not need to distinguish between buyers prior to an actual sale, does not require the information about the valuations of individual consumers or of consumer segments but allows consumers to self-select the product-price alternative instead (Bhargava and Choudhary 2001; Mussa and Rosen 1978).

2. Aim and overview of dissertation

The advantages of self-selection price differentiation with regard to the type and amount of information necessary for its successful application make this type of price differentiation easier and cheaper to implement in praxis (Philips 1989). Additionally, Khan and Jain (2005) who compare the effectiveness of price differentiation with and without self-selection show that the former performs better with regard to profitability (i.e., profit increase equal to 26% and 10% for price differentiation with and with no self-selection respectively compared to the situation when uniform pricing is applied). As a result, price differentiation with self-selection is more appealing and popular in praxis (Khan and Jain 2005). For these reasons, this dissertation focuses on self-selection price differentiation strategies.

While various forms of self-selection price differentiation have been mentioned in the previous chapter, continuous technological development provides opportunities for applying

existing forms in new areas or introducing new forms of self-selection price differentiation. On the one hand, the development and increasing popularity of the Internet brought in possibilities for novel pricing strategies such as online auctions or channel-based price differentiation. On the other hand, an increasing development of technologies that allow for monitoring customer usage (Whinston et al. 1997) and an enormous growth of service industries such as wireless communication and digital products (Iyengar et al. 2007) have led to new application areas and therefore great popularity of nonlinear pricing schemes (e.g., Danaher 2002; Essegaier et al. 2002; Iyengar et al. 2007; Lambrecht et al. 2007).

Due to these market trends, online pricing and nonlinear pricing strategies have received a lot of interest and attention from managers. Nevertheless, because of their novel applications, companies often experiment with these pricing strategies at great cost (Essegaier et al. 2002; Neslin et al. 2006) or avoid applying them and thus forgo the possibilities to increase the profit. As a result, it remains unclear to what extent companies take advantages of new possibilities of price differentiation and what may drive their decision to do so which calls for a research in this area (Neslin et al. 2006). Additionally, successful implementation of price differentiation requires an analysis of a consumer behavior in terms of his product valuation and subsequent behavior which also calls for a research in this area (Danaher 2002; Nunes 2000).

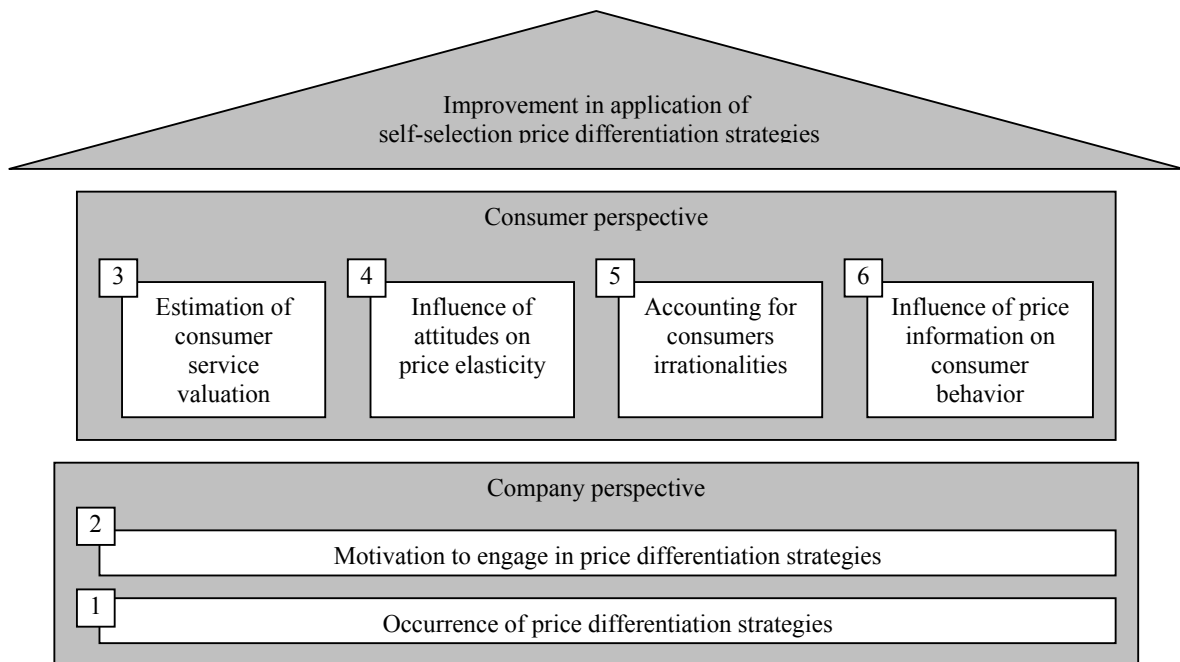
Therefore, the aim of this dissertation is to analyze various forms of self-selection price differentiation with a special focus on online pricing as well as nonlinear pricing from both company and consumer perspective in order to improve their successful application in new market areas. In order to accomplish that, I first analyze the extent to which companies apply various price differentiation strategies as well as the factors that influence company's decision to engage in price differentiation. Second, the consumer perspective is taken and consumer behavior under price differentiation is studied. The analysis based on transactional, survey and market data allows for deriving the managerial implications and recommendations with regard to self-selection price differential strategies.

In particular, this cumulative dissertation consists of 6 studies where various forms and aspects of self-selection price differentiation are analyzed (see also Figure 2):

- (1) Theysohn, S., Prokopowicz, A., and Skiera, B. (2005). Der Paid Content-Markt - Eine Bestandsaufnahme und Analyse von Preisstrategien. *Medienwirtschaft*, 4, 170-180.

- (2) Wolk, A. (2007a). Multi-Channel Pricing Strategy: To Price Differentiate or Not. Working Paper, University of Frankfurt.
- (3) Wolk, A., Skiera, B., and Schlereth, C. (2007). Augmented Methods of Conjoint Analysis to Estimate Willingness to Pay for Multiple-Unit Products, under review at Journal of Marketing Research.
- (4) Wolk, A., Lambrecht, A., and Skiera, B. (2007). The Influence of Tariff-Specific Preferences on Tariff Choice and Usage. Working Paper, University of Frankfurt.
- (5) Wolk, A. (2007b). Established Phenomenon or Occasional Incident? Persistence of Tariff-Choice Biases across Pricing Schemes, under review at Schmalenbach Business Review.
- (6) Wolk, A. and Spann, M. (2007). The Effects of Reference Prices on Bidding Behavior in Interactive Pricing Mechanisms, under review at Journal of Interactive Marketing.

Figure 2. Dissertation overview.



The first two studies focus on a company perspective and the price differentiation possibilities related to the Internet development. After gaining popularity among users, managers realized its great potential and started adopting the Internet as a distribution channel for trading both digital as well as physical goods. As a result, new possibilities for

price differentiation emerged. Study 1 analyzes the paid content market where digital goods are traded over the Internet and the extent to which various forms of price differentiation are applied in this new market.

Study 2 focuses on physical goods and analyzes traditional retailers that adopted the Internet as an additional distribution channel turning themselves into multi-channel retailers (Frazier 1999). The aim of this study is to analyze whether and to what extent multi-channel retailers engage in the channel-based price differentiation by charging differentiation prices in their online and offline channel and what influences the decision to do so. The results of two empirical studies show that although companies actively take advantage of existing market opportunities to engage in price differentiation, the applied practices may be suboptimal and should therefore be revised.

After analyzing company perspective, the focus of this dissertation turns toward consumer perspective. The growth of service industries such as digital goods has led to an increasing popularity of nonlinear pricing schemes. In fact, the results of study 1 have shown that nonlinear pricing is one the most popular methods used in this market. Since successful application of nonlinear pricing schemes requires a thorough understanding of consumer valuation and his subsequent behavior (Garbor 1988), study 3 proposes a method that uses survey data to estimate willingness-to-pay functions and shows how these willingness-to-pay functions can be used to analyze consumer behavior under nonlinear pricing schemes. Two empirical studies validate the proposed method.

While the analysis in study 3 assumes rational consumers who choose the tariff that minimizes their bill amount given their expected usage, study 4 relaxes this assumption and analyzes consumer behavior when accounting for tariff-specific preferences. Using both attitudinal data that measure latent preferences as well as transactional data, the influence of tariff-specific preferences on price sensitivity with respect to tariff choice and usage is analyzed.

Since study 4 shows that tariff-specific preferences have an influence on consumer behavior and his tariff choice, study 5 analyzes how these tariff-specific preferences can be profitably captured by an appropriate pricing strategy. Using survey data from four empirical studies, consumers are shown to be willing to additionally pay for their preferred tariff and an appropriate pricing scheme allows companies to skim this additional willingness to pay.

In addition to new applications of nonlinear pricing schemes, the Internet has also brought forward a set of novel interactive pricing mechanisms such as eBay auctions or name-your-own-price auctions which give consumers more control over the pricing process and the final price they have to pay. At the same time, however, this increased flexibility is related to considerable uncertainty about the product value, which consequently increases the effect of various forms of price information on consumer behavior. Consequently, study 6 analyzes consumer behavior in online reverse pricing auction and the influence of price information on the bid value, search behavior, and purchase intentions.

3. Dissertation studies

3.1. Paid content market – review and analysis of pricing strategies

While successful implementation of price differentiation may pose some difficulties in offline environment, a number of factors contribute to the possibilities of exercising price differentiation strategies in the context of the Internet. These factors include abundance of detailed customer data available in the Internet, technologies allowing for monitoring customer usage and according billing systems, as well as customization possibilities for digital goods (Shapiro and Varian 1998; Whinston et al. 1997). While these factors should lead to an increased application of various price differentiation strategies, it remains unclear to what extent the companies really exercise them.

Therefore, the aim of this project is to analyze the extent to which paid content providers take advantage of these new opportunities and apply price differentiation strategies when trading digital goods online. In the first step, we conduct expert interviews with paid content managers in order to identify the importance of pricing strategy and price differentiation in the overall marketing strategy. In the second step, we analyze the websites of 118 paid content providers and the pricing strategies they apply.

The results of expert interviews show that an appropriate pricing strategy has been identified as an important factor in order to achieve success in the paid content market. Price differentiation is especially a good strategy as 70% of paid content managers reported the usage of at least one form of price differentiation. Nonlinear pricing and versioning belong to most often used forms. Further, the analysis of paid content websites shows that paid content providers indeed regularly engage in at least one type of price differentiation (average 1.25 across all providers). Most often providers use quantity discounts (40% of the analyzed websites), followed by bundling (25%), versioning (23%), and optional tariffs (24%). While

self-selection price differentiation occurs relatively often, strategies with no self-selection are applied rather seldom (13%). This supports the notion that self-selection price differentiation methods are easier to implement and therefore more popular in the market.

The results of this study show that paid content providers use the opportunities created by online environment and often engage in more than one form of price differentiation. However, there is still unused potential in the German market compared to practices applied in American market.

3.2. Multi-channel pricing strategy: To price differentiate or not

Increasing popularity of the Internet and rapid growth of e-commerce have led many conventional retailers to initiate online sales and turn themselves into bricks-and-clicks retailers (Frazier 1999; Zettelmeyer 2000). Such a strategy gives consumers a possibility to choose between online and offline distribution channels when conducting a purchase. Since consumers perceive and value these channels differently (Chiang and Dholakia 2003; Kacen et al. 2003), an opportunity for applying channel-based price differentiation and charging differential prices for the same product in online and offline channels emerges.

Based on the existing literature, however, it remains unclear whether multi-channel retailers have recognized such an opportunity and whether channel-based price differentiation takes place in praxis. While theoretical work indicates for such a possibility (Dulleck and Kerschbamer 2005; Zettelmeyer 2000), existing empirical studies that focus on price dispersion in online and offline environment (e.g., Ancarani and Shankar 2004; Pan et al. 2002; Tang and Xing 2001) fail to find the evidence for that.

Consequently, the aim of this study is to analyze the occurrence of channel-based price differentiation among multi-channel retailers. Specifically, this study investigates whether multi-channel retailers charge the same or differential prices for the same product in their online and offline channel. Additionally, the study analyzes empirically the factors that influence company's decision to engage in price differentiation. While the topic received some attention in the economic literature (e.g., Salant 1989; Stokey 1979) where the authors develop analytical models to explain when a company engages in second-degree price discrimination, the empirical research in this area is very scarce.

The results of two empirical studies show that, in contrast to price dispersion literature, multi-channel retailers engage in channel-based price differentiation with the average price gap set as high as 13% of the product price. Although these results show that companies actively take

advantage of existing market opportunities to engage in price differentiation and thus increase the profits, the applied practices may be suboptimal and should therefore be revised. Additionally, various company and market factors have been found to influence the probability of engaging in channel-based price differentiation.

3.3. Augmented methods of conjoint analysis to estimate the willingness to pay for multiple-unit products

The growth of service industries and development of new technologies allowing for monitoring customer usage have led to an increasing interest for nonlinear pricing schemes (e.g., Danaher 2002; Essegai et al. 2002; Iyengar et al. 2007; Lambrecht et al. 2007). However, the analysis of nonlinear pricing schemes in case of pricing services poses many challenges and difficulties.

First of all, due to their distinctive cost structure pricing services should be based on users' valuations rather than traditional pricing policies based on costs (Gabor 1988; Whinston et al. 1997). While various methods have been developed in order to elicit willingness to pay for single-unit products (Wertenbroch and Skiera 2002), such multiple-unit products as services have been rather neglected. The challenge related to multiple-unit products is that more than one unit is usually bought and willingness to pay for various quantities that accounts for decreasing marginal willingness to pay needs to be estimated. Second of all, in order to develop an optimal pricing scheme, modeling consumer behavior should include not only purchase decision but also tariff choice and usage quantity decision. However, modeling consumer behavior under nonlinear pricing is very challenging due to the interdependency between tariff prices and the quantity in demand (Iyengar et al. 2007; Lambrecht et al. 2007; Train et al. 1987).

Therefore, in study 3 we propose to use willingness-to-pay functions (WTPF) to adequately capture the special characteristics of multiple-unit products and analyze consumer reactions under nonlinear pricing schemes. The aim of the study is to develop, validate and compare various methods that use survey data to estimate willingness-to-pay functions for multiple-unit products and show how they allow for the individual prediction of (i) the service purchase decision, (ii) the tariff choice decision and (iii) the usage quantity decision. Second, we compare various elicitation formats empirically in order to provide managerial recommendations with regard to most valid method. Third, we outline how the estimated willingness-to-pay functions allow for the prediction of the effects of different nonlinear

pricing schemes on the number of customers in the market ("market size effect"), the number of consumed units ("market volume effect") and the total revenue of the market ("market value effect").

The results of two empirical studies show that the proposed method leads to valid willingness-to-pay function estimates which can be subsequently used to evaluate nonlinear pricing schemes. Specifically, we show how price changes affect revenue by analyzing a "market expansion effect" (new or lost customers in the market), a "switching effect" (new or lost customers swapped from or to competitors), and a "cannibalization effect" (change in behavior of the current customers).

3.4. The influence of tariff preferences on tariff choice and usage

In study 3 we follow the standard economic theory that assumes that consumers pick a tariff that maximizes their expected consumer surplus. Consequently, consumers are expected to choose a tariff that minimizes the bill amount given their expected usage. However, empirical studies show that consumers often choose a tariff that does not minimize their bill amount implying that consumers may develop tariff-specific preferences (Lambrecht and Skiera 2006; Nunes 2000).

Since attitudes guide behavior, these tariff-specific preferences are likely to have an influence on consumers' behavior and their price responsiveness. While price sensitivities are very important for a company to set optimal prices, Danaher (2002) argues that there is still insufficient understanding of their role in subscription services. For example, existing studies assume that consumers are homogeneous with regard to their price sensitivity and neglect the influence of tariff preferences on consumers' price responsiveness (Kling and Ploeg 1990; Lambrecht et al. 2007; Lee 1999; Train et al. 1987). As a result of ignoring consumer heterogeneity existing research fail to recognize the existence of various consumer segments and may lead to suboptimal recommendations for pricing strategy.

Consequently, the objective of this paper is to analyze the influence of tariff-specific preferences on price sensitivity with respect to tariff choice and usage. Therefore, we first study to what extent consumers have heterogeneous tariff-specific preferences and then we analyze how those tariff-specific preferences influence price elasticities. A key feature of our approach is that we combine actual usage data with attitudinal data from a survey of the same consumers. Based on attitudinal data we identify consumer segments that differ in their tariff-

specific preferences. The transactional data then allow us to estimate price elasticities of tariff choice and usage for each segment.

The results show that tariff-specific preferences indeed affect price elasticity. Specifically, consumers with tariff-specific preferences are less sensitive to the price increase of their preferred tariffs. Further, increase in tariff prices has a stronger negative effect on usage quantity in the flat-rate aversion segment than in the flat-rate preference segment that is more likely to switch to tariffs with higher allowance. Lastly, we show that consumers with tariff-specific preferences are more likely to adjust their usage in response to the price increase while consumers with no tariff-specific preferences are more likely to adjust their tariffs. These differences in price elasticities support the usage of optional tariffs rather than uniform nonlinear pricing schemes.

3.5. Established phenomenon or occasional incident? Persistence of tariff-choice biases across pricing schemes

Study 4 shows that consumers often develop tariff-specific preferences which in addition to the bill amount drive their tariff choice. In particular, tariff-specific preferences lead to a lower sensitivity to the price increase of the preferred tariff. Such lower price sensitivity may even result in consumers choosing the tariff that does not minimize their bill amount. In fact, empirical studies have shown that there are consumers that choose a flat rate even though a pay-per-use tariff would lead to a lower bid and they are argued to have a flat-rate bias (Nunes 2000; Train et al. 1987). On the other hand, consumers that choose a pay-per-use tariff even though under a flat rate they would pay less are claimed to have a pay-per-use bias (Lambrecht and Skiera 2006).

While tariff-choice biases are well recognized in the literature, it remains unclear how persistent they are across varying pricing schemes and whether the extent of their occurrence would be the same under different pricing schemes. The occurrence of tariff-choice biases is, however, of high importance for a company, because it may increase its profits (Lambrecht and Skiera 2006). Therefore, it is of high interest to analyze whether company pricing strategy influences the extent of tariff-choice bias occurrence (Nunes 2000).

Consequently, the aim of this paper is to analyze the persistence of tariff-choice biases across varying pricing schemes. First, it is analyzed whether consumers continually choose a wrong tariff across varying pricing schemes. Second, the effect of tariff prices (i.e., a fixed fee and a marginal price) and break-even point on the tariff-choice bias occurrence is investigated.

Third, the paper shows how a pricing scheme can be set in order to better skim consumer willingness to pay for a preferred tariff.

The results of four empirical studies shows that tariff-choice biases are sensitive to pricing schemes and tariff prices as well as the resulting break-even point significantly influence the probability of a tariff-choice bias occurrence. Furthermore, the results show that many consumers may be potentially willing to pay more for their preferred tariff; however, the company loses this potential profit if the pricing scheme is not adequately designed. Managerial implications that allow to better skim tariff-specific willingness to pay are derived.

3.6. The effects of reference prices on bidding behavior in interactive pricing mechanisms

The development and popularity of the Internet has led many companies to incorporate it in their business model and initiate novel business strategies. Studies 1 and 2 show that companies adopt the Internet as a distribution channel and engage in channel-based price differentiation. In addition to changes in the distribution system, the Internet has also led to the emergence of a set of interactive pricing mechanisms, such as eBay auctions (e.g. eBay.com) or name-your-own-price auctions (e.g. priceline.com, expedia.com, germanwings.com), which are constantly gaining popularity among consumers and retailers (Bapna 2005).

The distinctive characteristic of these mechanisms is that they give consumers more control over the price setting process and the final price to pay in that they require consumers to determine the value of their bid for the product. This flexibility is, however, related to considerable uncertainty about the product value (Chernev 2003), which increases the importance of price information, such as reference price, in the consumer decision making process.

While the role of reference prices has been extensively analyzed in the offline posted-price scenario, the research in online auctions is rather scarce. Additionally, the results from the offline posted-price scenario cannot be directly transferred to online auction, because the role of reference prices changes in the interactive pricing mechanisms. Nevertheless, since reference price may influence the bid value as well as purchase decision, knowing its effect is of high importance for online auction managers. Therefore, the aim of this paper is to analyze the effect of a reference price on bidding behavior in one specific interactive pricing mechanism, the name-your-own-price auction, with respect to the bid value, search behavior,

and purchase intentions. In contrast to previous studies, we distinguish between three reference price concepts, namely an internal, an external and an advertised reference price, and we determine their effect on bid values.

The results of the empirical study show significant influence of different reference price concepts on bid values, which provides the evidence that with regard to product valuation the effects of reference prices are robust across various purchase scenarios. Nevertheless, the seller-provided advertised reference price seems to have a lower effect in online auctions than in offline environment. In contrast, with regard to search behavior and purchase intentions we extend previous results and show how the role of reference prices changes in interactive pricing scenarios.

4. Summary

Self-selection price differentiation encompasses a broad range of various pricing strategies. Their common characteristic is that companies offer consumers a choice of various product-price combinations and allow them to self-select the option that best meets their preferences. In this dissertation I analyze various forms of self-selection price differentiation strategies from company and consumer perspective and show how technological developments allow for new applications and new forms of self-selection price discrimination strategies.

This dissertation provides both academic and managerial contributions (see Table 1). In terms of academic contribution, it analyzes the extent of price differentiation application in the market and tests empirically the microeconomic theory with respect to the requirements and motivation for engaging in price differentiation. From the consumer perspective, it proposes, tests and compares various methods for willingness-to-pay function estimation in the context of multiple-unit products. Additionally, in the context of nonlinear pricing it accounts for heterogeneity in consumer tariff-specific preferences when modeling consumer behavior under optional tariffs and tests the robustness of tariff-choice biases. Lastly, it analyses the effect of three different reference price concepts on consumer behavior in online auction and as such contributes to both reference price as well as online auction literature.

In addition to academic insights, this dissertation provides many managerial implications. First, it shows that there is an unexplored potential for engaging in price differentiation in online environment with respect to digital goods. Second, it shows a suboptimal application of channel-based price differentiation and as such calls for a revision in this area. Further, this dissertation provides a tool for analyzing the effect of nonlinear pricing schemes on market

size, market volume and market value as well as decomposing the profit changes into market expansion effect, switching effect, and cannibalization effect. As such it allows for evaluating various pricing strategies. In the context of nonlinear pricing it further provides insights how to profitably account for tariff-specific preferences and tariff-choice biases. Lastly, it provides recommendations regarding the price information that should be provided by online auction managers.

Table 1. Contribution of dissertation studies.

| Paper | Contribution | Managerial insights |
|---|--|---|
| 1 Paid content market – review and analysis of pricing strategies | Empirical analysis of price differentiation strategies in paid content market | Potential for more complex pricing strategies in online environment |
| 2 Multi-channel pricing strategy: To price differentiate or not | Empirical analysis of factors that influence the decision to engage in price differentiation strategy | Potential for engaging in channel-based price differentiation for big companies with market power; insights for improving current multi-channel pricing practices |
| 3 Augmented methods of conjoint analysis to estimate the willingness to pay for multiple-unit products | Development, validation and comparison of various methods that use survey data to estimate willingness-to-pay function for multiple-unit products | Influence of nonlinear pricing scheme on market size, volume and value; deposition of profit changes due to price differences |
| 4 The influence of tariff-specific preferences on tariff choice and usage | Influence of tariff-specific preferences on price elasticity of tariff choice and usage; accounting for consumer heterogeneity in tariff choice decision | Recommendation for optional nonlinear pricing tariffs rather than using uniform tariffs when pricing services |
| 5 Established phenomenon or occasional incident? Persistence of tariff-choice biases across pricing schemes | Regularity and robustness of tariff-choice biases; influence of pricing scheme on tariff-choice bias occurrence | Insights into pricing strategy that would allow to skim willingness to pay for preferred tariffs |
| 6 The effects of reference prices on bidding behavior in interactive pricing mechanisms | Effect of various concepts of reference price on consumer behavior in interactive pricing mechanisms | Recommendations with regard to necessary price information on the online auction website |

References

- Ancarani, F., & Shankar, V. (2004). Price Levels and Price Dispersion Within and Across Multiple Retailer Types: Further Evidence and Extension. *Journal of the Academy of Marketing Science*, 32(2), 176-187.
- Bapna, R. (2005). Consumer Surplus in Online Auctions. Working Paper, University of Connecticut.
- Bhargava, H. K., & Choudhary, V. (2001). *Second-Degree Price Discrimination for Information Goods Under Nonlinear Utility Functions*. Paper presented at the Proceedings of the 34th Hawaii International Conference on System Sciences.
- Chernev, A. (2003). Reverse Pricing and Online Price Elicitation Strategies in Consumer Choice. *Journal of Consumer Psychology*, 13(1&2), 51-62.
- Chiang, K.-P., & Dholakia, R. R. (2003). Factors Driving Consumer Intention to Shop Online: An Empirical Investigation. *Journal of Consumer Psychology*, 13(1&2), 177-183.
- Chintagunta, P. K., Dubé, J.-P., & Singh, V. (2003). Balancing Profitability and Customer Welfare in a Supermarket Chain. *Quantitative Marketing and Economics*, 1(1), 111-147.
- Cohen, A. (2002). Package Size and Price Discrimination in Paper Towels. Working Paper, University of Virginia.
- Danaher, P. J. (2002). Optimal Pricing of New Subscription Services: Analysis of a Market Experiment. *Marketing Science*, 21(2), 119-138.
- Deneckere, R. J., & McAfee, R. P. (1996). Damaged Goods. *Journal of Economics and Management Strategy*, 5(2), 149-174.
- Dobson, G., & Kalish, S. (1988). Positioning and Pricing a Product Line. *Marketing Science*, 7(2), 107-125.
- Dolan, R. J. (1987). Quantity Discounts: Managerial Issues and Research Opportunities. *Marketing Science*, 6(1), 1-23.
- Draganska, M., & Jain, D. C. (2006). Consumer Preferences and Product-Line Pricing Strategies: An Empirical Analysis. *Marketing Science*, 25(2), 164-174.
- Dulleck, U., & Kerschbamer, R. (2005). Price Discrimination via the Choice of Distribution Channels. Working Paper, Johannes Kepler University of Linz.
- Elrod, T., & Winer, R. S. (1982). An Empirical Evaluation of Aggregation Approaches for Developing Market Segments. *Journal of Marketing*, 46(Fall), 64-74.

- Essegaier, S., Gupta, S., & Zhang, Z. J. (2002). Pricing Access Services. *Marketing Science*, 21(2), 139-159.
- Frazier, G. F. (1999). Organizing and Managing Channels of Distribution. *Journal of Academy of Marketing Science*, 27(2), 226-240.
- Gabor, A. (1988). *Pricing: Concepts and Methods of Effective Marketing*. England: Gower.
- Gijsbrechts, E. (1993). Prices and Pricing Research in Consumer Marketing: Some Recent Developments. *International Journal of Research in Marketing*, 10(2), 115-151.
- Hoch, S. J., Kim, B.-D., Montgomery, A. L., & Rossi, P. E. (1995). Determinants of Store-Level Price Elasticity. *Journal of Marketing Research*, 32(February), 17-29.
- Iyengar, R., Jedidi, K., & Kohli, R. (2007). A Conjoint Approach to Multi-Part Pricing. *Journal of Marketing Research*, forthcoming.
- Jain, S., & Srivastava, Y. (2000). An Experimental and Theoretical Analysis of Price-Matching Refund Policies. *Journal of Marketing Research*, 37(August), 351-362.
- Jensen, T., Kees, J., Burton, S., & Turnipseed, F. L. (2003). Advertised Reference Prices in an Internet Environment: Effects on Consumer Price Perceptions and Channel Search Intentions. *Journal of Interactive Marketing*, 17(2), 20-33.
- Kacen, J. J., Hess, J. D., & Chiang, W.-y. K. (2003). Bricks or Clicks? Consumer Attitudes Toward Traditional Stores and Online Stores. Working Paper, University of Houston.
- Kahn, C. (1986). The Durable Goods Monopolist and Consistency with Increasing Costs. *Econometrica*, 54(2), 275-294.
- Kamins, M. A., Dreze, X., & Folkes, V. S. (2004). Effects of Seller-Supplied Prices on Buyers' Product Evaluations: Reference Prices in an Internet Auction Context. *Journal of Consumer Research*, 30(March), 621-628.
- Khan, R. J., & Jain, D. C. (2005). An Empirical Analysis of Price Discrimination Mechanisms and Retailer Profitability. *Journal of Marketing Research*, 42(4), 516-524.
- Kling, J. P., & Ploeg, S. S. v. d. (1990). Estimating Local Elasticities with a Model of Stochastic Class of Service and Usage Choice. In A. d. Fontenay & M. H. Shugard & D. S. Sibley (Eds.), *Telecommunications Demand Modelling. An Integrated View*. Amsterdam: North Holland.
- Lambrecht, A., Seim, K., & Skiera, B. (2007). Does Uncertainty Matter? Consumer Behavior under Three-Part Tariffs. *Marketing Science*, forthcoming.

- Lambrecht, A., & Skiera, B. (2006). Paying Too Much and Being Happy About It: Causes and Consequences of Tariff-Choice Biases. *Journal of Marketing Research*, 43(2), 212-223.
- Lancaster, K. (1990). The Economics of Product Variety: A Survey. *Marketing Science*, 9(3), 189-206.
- Lee, B. (1999). Calling Patterns and Usage of Residential Toll Service under Self Selecting Tariffs. *Journal of Regulatory Economics*, 16(1), 45-81.
- Leslie, P. (2004). Price Discrimination in Broadway Theater. *RAND Journal of Economics*, 35(3), 520-541.
- Marn, M. V., Roenger, E. V., & Zawada, C. C. (2004). *The Price Advantage*. Hoboken, N. J.: Wiley.
- Montgomery, A. L. (1997). Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data. *Marketing Science*, 16(4), 315-337.
- Moorthy, K. S. (1984). Market Segmentation, Self-Selection, and Product Line Design. *Marketing Science*, 2(4), 288-305.
- Mussa, M., & Rosen, S. (1978). Monopoly and Product Quality. *Journal of Economic Theory*, 18(2), 301-317.
- Narasimhan, C. (1984). A Price Discrimination Theory of Coupons. *Marketing Science*, 3(2), 128-147.
- Neslin, S. A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M. L., Thomas, J. S., & Verhoef, P. C. (2006). Challenges and Opportunities in Multichannel Customer Management. *Journal of Service Research*, 9(2), 95-112.
- Nunes, J. (2000). A Cognitive Model of People's Usage Estimations. *Journal of Marketing Research*, 37(November), 397-409.
- Oi, W. Y. (1971). A Disneyland Dilemma: Two-Part Tariffs for a Mickey Mouse Monopoly. *Quarterly Journal of Economics*, 85, 77-96.
- Pan, X., Ratchford, B. T., & Shankar, V. (2004). Price Dispersion on the Internet: A Review and Directions for Future Research. *Journal of Interactive Marketing*, 18(4), 116-135.
- Phlips, L. (1989). *The Economics of Price Discrimination*. Cambridge et al.: Cambridge University Press.
- Pigou, A. C. (1920). *The Economics of Welfare*. London: MacMillan.
- Png, I. P. L., & Hirshleifer, D. (1987). Price Discrimination through Offers to Match Prices. *Journal of Business*, 60(3), 365-383.

- Rao, V. R. (1984). Pricing Research in Marketing: The State of the Art. *Journal of Business*, 57(1), S39-S69.
- Reibstein, D. J., & Gatignon, H. (1984). Optimal Product Line Pricing: The Influence of Elasticities and Cross-Elasticities. *Journal of Marketing Research*, 21(3), 259-267.
- Rossi, P. E., & Allenby, G. M. (1993). A Bayesian Approach to Estimating Household Parameters. *Journal of Marketing Research*, 30(May), 171-182.
- Salant, S. W. (1989). When Is Inducing Self-Selection Suboptimal for a Monopolist? *Quarterly Journal of Economics*, 104(2), 391-397.
- Schulze, T., & Gedenk, K. (2005). Biases bei der Tarifwahl und ihre Konsequenzen für die Preisgestaltung. *Zeitschrift für Betriebswirtschaft*, 75, 157-184.
- Shaked, A., & Sutton, J. (1987). Product Differentiation and Industrial Structure. *Journal of Industrial Economics*, 36(2), 131-146.
- Shapiro, C., & Varian, H. R. (1998). Versioning: The Smart Way to Sell Information. *Harvard Business Review*, 76(6), 106-114.
- Simon, H. (1992). *Preismanagement*. Wiesbaden: Gabler.
- Skiera, B. (1999). Mengenbezogene Preisdifferenzierung bei Dienstleistungen. Wiesbaden.
- Spann, M., Fischer, M., & Tellis, G. J. (2007). Skimming or Penetration? Test of Dynamic Pricing Strategies for New Products. Working Paper, Passau University.
- Spann, M., & Tellis, G. J. (2006). Does the Internet Promote Better Consumer Decisions? The Case of Name-Your-Own-Price Auctions. *Journal of Marketing*, 70(1), 65-78.
- Stokey, N. L. (1979). Intertemporal Price Discrimination. *Quarterly Journal of Economics*, 93(3), 355-371.
- Tacke, G. (1989). *Nichtlineare Preisbildung: Höhere Gewinne durch Differenzierung*. Wiesbaden: Gabler.
- Tang, F.-F., & Xing, X. (2001). Will the Growth of Multi-Channel Retailing Diminish the Pricing Efficiency of the Web? *Journal of Retailing*, 77(3), 319-333.
- Tellis, G. (1986). Beyond the Many Faces of Price: An Integration of Pricing Strategies. *Journal of Marketing*, 50(October), 146-160.
- Theysohn, S., Prokopowicz, A., & Skiera, B. (2005). Der Paid Content-Markt - Eine Bestandsaufnahme und Analyse von Preisstrategien. *Medienwirtschaft*, 4, 170-180.
- Train, K. E., McFadden, D. L., & Ben-Akiva, M. (1987). The Demand for the Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *Rand Journal of Economics*, 18(1), 109-123.

- Wertenbroch, K., & Skiera, B. (2002). Measuring Consumers' Willingness to Pay at the Point of Purchase. *Journal of Marketing Research*, 39(2), 228-241.
- Whinston, A. B., Stahl, D. O., & Choi, S.-Y. (1997). *The Economics of Electronic Commerce*. Indianapolis: Macmillan Technical Publishing.
- Wilson, R. (1993). *Nonlinear Pricing*. New York et al.: Oxford University Press.
- Wolk, A. (2007a). Multi-Channel Pricing Strategy: To Price Differentiate or Not. Working Paper, University of Frankfurt.
- Wolk, A. (2007b). Established Phenomenon or Occasional Incident? Persistence of Tariff-Choice Biases across Pricing Schemes. Working Paper, University of Frankfurt.
- Wolk, A., Lambrecht, A., & Skiera, B. (2007). The Influence of Tariff Preferences on Tariff Choice and Usage. Working Paper, University of Frankfurt.
- Wolk, A., Skiera, B., & Schlereth, C. (2007). Augmented Methods of Conjoint Analysis to Estimate Willingness to Pay for Multiple-Unit Products. Working Paper, University of Frankfurt.
- Wolk, A., & Spann, M. (2007). The Effects of Reference Prices on Bidding Behavior in Interactive Pricing Mechanisms. under review at *Journal of Interactive Marketing*.
- Xie, J., & Shugan, S. M. (2001). Electronic Tickets, Smart Cards, and Online Prepayments: When and How to Advance Sell. *Marketing Science*, 20(3), 219.
- Zettelmeyer, F. (2000). Expanding to the Internet: Pricing and Communication Strategies When Firms Compete on Multiple Channels. *Journal of Marketing Research*, 37(3), 292-308.

Der Paid Content-Markt – Eine Bestandsaufnahme und Analyse von Preisstrategien

Sven Theysohn

Agnieszka Prokopowicz

Bernd Skiera

Theysohn, S., Prokopowicz, A., and Skiera, B. (2005). Der Paid Content-Markt - Eine Bestandsaufnahme und Analyse von Preisstrategien. *Medienwirtschaft*, 4, 170-180.

Der Paid Content-Markt – Eine Bestandsaufnahme und Analyse von Preisstrategien

Abstrakt

Der Paid Content-Markt verzeichnete in den letzten vier Jahren sowohl in Deutschland als auch in den USA ein enormes Wachstum. Treiber dieser Entwicklung sind Angebote in den Bereichen „Information“ (z.B. journalistische Inhalte, Wirtschaftsinformationen) und „persönliche Dienstleistungen“ (z.B. Dating-Angebote, Ernährungsberatung) in den USA sowie „Information“ und „Entertainment“ (z.B. Musik, Spiele, Handy Downloads) in Deutschland. Ziel dieses Beitrags ist es, eine Bestandsaufnahme von Anbietern, Produktkategorien und Zahlungsbereitschaften im deutschen und US-amerikanischen Paid Content-Markt vorzunehmen und den Einfluss der Preisdifferenzierung als zentralen Teil der Preisstrategie von Unternehmen auf den Markterfolg zu analysieren. Es wird gezeigt, dass die Preisdifferenzierung aufgrund der Unterschiede in den Zahlungsbereitschaften der Konsumenten eine erfolgsversprechende Preisstrategie darstellt. Die Mehrzahl der am Markt befindlichen Unternehmen wenden bereits verschiedene Formen der Preisdifferenzierung an, wobei die Preisdifferenzierung mit Selbstselektion dominiert. Verglichen mit dem deutschen Paid Content-Markt kann eine wesentlich höhere Anwendung der mehrdimensionalen Preisdifferenzierung und damit eine feinere Segmentierung der Konsumenten im US-amerikanischen Paid Content-Markt festgestellt werden.

Schlüsselbegriffe: Paid Content, Preisgestaltung, Preisdifferenzierung, Internet, Zahlungsbereitschaft.

1. Problemstellung

Der Paid Content-Markt konnte sowohl in Deutschland als auch in den USA während der vergangenen vier Jahre ein starkes Wachstum verzeichnen (Oelbermann und v. Reibnitz 2003; Online Publishers Association 2005). Die ebenfalls zunehmende Zahl an Breitbandnutzern (Point Topic Information rules - A Strategic Guide to the Network Economy 2005) und die steigende Bereitschaft unter diesen Internetnutzern zum käuflichen Erwerb digitaler Produkte (Stern 2005) lassen hoffen, dass sich für Paid Content-Anbieter die Etablierung von transaktionsbasierten Erlösmodellen vereinfacht. Doch trotz der positiven Marktentwicklung in den letzten Jahren fällt es der Mehrzahl der Paid Content-Anbieter weiterhin schwer, für ein digitales Produktangebot eine entsprechende monetäre Gegenleistung durchzusetzen. Werbefinanzierte Erlösmodelle sind mit weitem Abstand die dominierende Erlösquelle (BVDW 2004; Oelbermann und v. Reibnitz 2003), da unter den Internetnutzern die „for free“ Mentalität immer noch weit verbreitet ist. Sie sind also noch nicht bereit, für den Erwerb digitaler Produkte zu bezahlen.

Ziel dieses Beitrags ist es, eine Bestandsaufnahme von Anbietern und Produktkategorien im deutschen und US-amerikanischen Paid Content-Markt vorzunehmen sowie Unterschiede in den Zahlungsbereitschaften der Konsumenten darzustellen. Darauf aufbauend wird der Einfluss der Preisdifferenzierung als zentraler Teil der Preisstrategie von Unternehmen auf den Markterfolg analysiert. Hierbei wird speziell auf die verbesserten Möglichkeiten der Umsetzung verschiedener Formen der ein- und mehrdimensionalen Preisdifferenzierung (Mengenrabatte, Preisbündelung, Versioning, Tarifwahl, Segmentierung) durch den Einsatz von Informationstechnologie eingegangen (z.B., Geng et al. 2005; Hitt und Chen 2005; Lambrecht und Skiera 2006; Skiera 2001; Skiera et al. 2005; Sundararaja 2004). Betrachtet werden der zurzeit größte Paid Content-Markt USA sowie der deutsche Paid Content-Markt.

Der weitere Aufbau des Beitrags ist wie folgt: In Kapitel 2 wird zunächst die Definition der Begrifflichkeiten, eine Beschreibung des US-amerikanischen und deutschen Paid Content-Marktes, eine Produktkategorisierung und die Analyse der Zahlungsbereitschaft von potenziellen Konsumenten mittels Experteninterviews und der Auswertung bestehender Studien vorgenommen. Kapitel 3 beschreibt die Bedeutung der Preispolitik aus Sicht der am Markt befindlichen Unternehmen sowie die Bedeutung und Umsetzung der ein- und mehrdimensionalen Preisdifferenzierung anhand von Experteninterviews und Analysen von Webseiten. Kapitel 4 fasst die gewonnen Erkenntnisse zusammen und leitet Implikationen für die Unternehmenspraxis ab.

2. Paid Content

2.1. Definition und Klassifizierung digitaler Produkte

Im Rahmen dieser Studie werden käuflich zu erwerbende Produkte als Paid Content definiert, bei denen Erstellung, Vertrieb und Abrechnung zwischen Unternehmen (B2B) oder zwischen Unternehmen und Kunden (B2C) digital erfolgen (Shapiro und Varian 1999; Whinston et al. 1997). Tabelle 1 nimmt eine Klassifizierung des Paid Content-Marktes anhand der Produktkategorie und der für den digitalen Vertrieb bedeutenden Dimension Netzwerk vor.

Tabelle 1. Klassifizierung des Paid Content-Marktes.

| | | Netzwerk | |
|-----------------------|----------------------------|--|--|
| | | offen | geschlossen |
| Produkt- kategorie | Digitale Güter | 1 | 4 |
| | | Verbrauchs- güter | Börseninformationen, Befristete Software-Lizenzen, Antiviren-programme |
| | Gebrauchs- güter | 2 | 5 |
| | | Sportstatistiken, Musik Downloads, E-books | Content Syndication, B2B Databanken (z.B. zum Informationsaustausch) |
| | Digitale Serviceleistungen | 3 | 6 |
| | | Online Banking, Dating, Auktionsplattformen | SABRE Flug-Buchungssystem, Börsen-Handelssystem (XETRA) |

Digitale Produkte können demnach in die drei Subkategorien digitales Gebrauchsgut, digitales Verbrauchsgut und digitale Serviceleistung aufgeteilt werden. Digitale Verbrauchsgüter bestehen aus digitalen Inhalten, die dem Anwender für einen befristeten Zeitraum die Ausführung spezifischer Handlungen ermöglicht (z.B. Antiviren-Software, Statistikprogramme). Als digitale Gebrauchsgüter werden digitale Inhalte bezeichnet, deren Nutzung zeitlich nicht begrenzt ist (z.B. PC-Betriebssysteme, Musik Downloads, E-Books). Digitale Serviceleistungen beschreiben die Bereitstellung eines Online-Dienstleistungsangebots (z.B. eine Plattform zur Abwicklung von Online-Transaktionen) sowie die Bereitstellung von Online-Funktionalitäten zur Ausübung spezifischer Tätigkeiten (z.B. Online-Buchung von Flügen).

Die Dimension Netzwerk bezieht sich auf die notwendige Infrastruktur zum Vertrieb von digitalen Produkten. Netzwerke besitzen aufgrund verschiedener Verwendungszwecke unterschiedliche Ausprägungen, welche im Wesentlichen die Eigenschaften Informationssuche, Datenaustausch und Sicherheitsstandards betreffen. Offene Netzwerke,

z.B. das Internet, bieten einen Zugang für alle Käufer und Verkäufer, die entsprechende technische Mindestvoraussetzungen erfüllen, bieten aber nur geringe Sicherheitsstandards. Geschlossene Netzwerke, z.B. Extranets oder Virtual Private Networks, weisen entsprechend gegenläufige Eigenschaften auf. Sie sind zwar wesentlich sicherer und zuverlässiger, es ist jedoch in der Regel nicht möglich, jeden potenziellen Geschäftspartner zu erreichen.

Im Folgenden werden mittels Expertengesprächen, bestehender Marktanalysen sowie einer Analyse von Webseiten digitale Produkte für offene Netzwerke untersucht. Die Verwendung des Begriffs Paid Content im weiteren Verlauf dieser Arbeit bezieht sich also auf Unternehmen in den Teilmärkten 1 – 3 der Tabelle 1. Das Produktangebot innerhalb dieser Teilmärkte kann inhaltlich in die in Tabelle 2 beschriebenen fünf Kategorien unterteilt werden, wobei beispielhaft einige deutsche und US-amerikanische Anbieter aufgeführt werden.

Tabelle 2. Produktkategorisierung für den Paid Content-Markt.

| Kategorien | Subkategorien | Beispiele für Produkthanbieter |
|----------------------------------|--|--|
| Multiple content providers (A) | | yahoo.com, msn.com, web.de, t-online.de, freenet.de |
| Persönliche Dienstleistungen (B) | Dating-Angebote | match.com, singles.com, friendscout24.de, ilove.de |
| | Ernährungsberatung | weightwatchers.com, ediets.com, cyberdiet.com |
| | Verzeichnisse | classmates.com, ancestry.com, imdb.com, openbc.com |
| | E-Mail Premium Service | yahoo.com, hotmail.com, gmx.de, web.de |
| | Andere | Therapeut: therapy-online.com, etherapistonline.com Horoskop: myastrologyadvisor.com, astrology.com |
| Entertainment (C) | Musik | napster.com, musicnet.com, itunes.com, popfile.de, bmg.de |
| | Spiele (Quiz) | everquest.com, gamerival.com, casesladder.com, lotto.de |
| | Grußkarten | americangreetings.com, bluemountain.com, hallmark.com |
| | E-books | internetbooks.de, reclam.de |
| | Handy Downloads | jamba.de, mload.de, t-mobile.de |
| | Erotik | playboy.com, nerve.com, beate-uhse.de, hotjoy.de |
| | Andere | Photogalerien: live-sportphotos.com |
| Information (D) | Journalistische Inhalte | wsj.com, nytimes.com, cnn.com, usatoday.com, spiegel.de |
| | Wirtschaftsinformationen | thestreet.com, emarketer.com, onvista.de |
| | Konsumenteninformationen | consumerreports.com, stiftungwarentest.de |
| | Enzyklopädie/Wörterbuch | britannica.com, encarta.msn.com |
| | Wetterinformationen | weather.com, accuweather.com, wetter.de |
| | Sportinformationen | espn.com, sportingnews.com, mlb.com, sportsline.com |
| | Andere | Geographische Informationen: falk.de |
| Forschung (E) | Elektronische Büchereien und Datenbanken | elibrary.com, highbeam.com |

2.2. Darstellung der Marktentwicklung des Paid Content-Angebots

Nachdem in den USA die Einnahmen aus Paid Content in den Jahren 2001 und 2002 um jeweils ca. 100% gestiegen sind, betrug das Wachstum 2003 und 2004 auch aufgrund der schwachen konjunkturellen Lage 19,9 bzw. 13,7%. Das Gesamtmarktvolumen wird Anfang 2005 von der Online Publishers Association (Online Publishers Association 2005) auf 1,8 Milliarden US Dollar geschätzt. Ebenfalls ansteigend ist die Bereitschaft unter US-amerikanischen Internetnutzern zum käuflichen Erwerb digitaler Produkte. Während bereits 27% der Internetnutzer nicht-digitale Produktkäufe über das World Wide Web getätigt haben, liegt die Anzahl der Paid Content-Konsumenten Ende 2004 immerhin bei ca. 11,6%, mit stark steigender Tendenz (Online Publishers Association 2005). Tabelle 3 zeigt die von der Online Publishers Association nur von 2001 bis 2003 durchgeführte Ermittlung der Top 25 Anbieter von Paid Content auf dem US-amerikanischen Markt:

Tabelle 3. Überblick über die Top 25 Anbieter aus den Jahren 2001, 2002 und 2003.

| Top 25-Ranking | 2001 | | | 2002 | | | 2003 | | |
|----------------|---------------------|---|----|---------------------|---|----|---------------------|---|----|
| | Anbieter | K | R | Anbieter | K | R | Anbieter | K | R |
| 1. | real.com | C | 1 | yahoo.com | A | 1 | yahoo.com | A | 1 |
| 2. | wsj.com | D | 2 | match.com | B | 2 | real.com | C | 2 |
| 3. | match.com | B | 3 | real.com | C | 3 | match.com | B | 3 |
| 4. | yahoo.com | A | 4 | Classmates.com | B | 4 | classmates.com | B | 4 |
| 5. | consumerreports.org | D | 5 | wsj.com | D | 5 | wsj.com | D | 5 |
| 6. | ancestry.com | B | 6 | weightwatchers.com | B | 6 | ediets.com | B | 6 |
| 7. | weightwatchers.com | B | 7 | ancestry.com | B | 7 | matchmaker.com | B | 7 |
| 8. | 1800ussearch.com | B | 8 | consumerinfo.com | D | 8 | weightwatchers.com | B | 8 |
| 9. | matchmaker.com | B | 9 | matchmaker.com | B | 9 | consumerreports.org | D | 9 |
| 10. | consumerinfo.com | D | 10 | 1800ussearch.com | B | 10 | 1800ussearch.com | B | 10 |
| 11. | ieee.org | D | 11 | consumerreports.org | D | 11 | kiss.com | B | 11 |
| 12. | classmates.com | B | 12 | espn.go.com | D | 12 | ancestry.com | B | 12 |
| 13. | playboy.com | C | 13 | carfax.com | D | 13 | bluemountain.com | C | 13 |
| 14. | thetstreet.com | D | 14 | thetstreet.com | D | 14 | carfax.com | D | 14 |
| 15. | msn.com | A | 15 | bluemountain.com | C | 15 | playboy.com | C | 15 |
| 16. | kiss.com | B | 16 | playboy.com | C | 16 | pressplay.com | C | 16 |
| 17. | espn.go.com | D | 17 | kiss.com | B | 17 | espn.go.com | D | 17 |
| 18. | carfax.com | D | 18 | msn.com | A | 18 | ieee.org | D | 18 |
| 19. | hallmark.com | C | 19 | egreetings.com | C | 19 | egreetings.com | C | 19 |
| 20. | bluemountain.com | C | 20 | ieee.org | D | 20 | msn.com | A | 20 |
| 21. | arttoday.com | D | 21 | arttoday.com | D | 21 | astrology.com | B | 21 |
| 22. | britannica.com | D | 22 | pressplay.com | C | 22 | thetstreet.com | D | 22 |
| 23. | elibrary.com | E | 23 | britannica.com | D | 23 | britannica.com | D | 23 |
| 24. | changewave.com | D | 24 | astrology.com | B | 24 | consumerinfo.com | D | 24 |
| 25. | smartmoney.com | D | 25 | smartmoney.com | D | 25 | smartmoney.com | D | 25 |

(Quelle: Online Publishers Association 2003; Online Publishers Association 2004)

Dominierend sind die Kategorien persönliche Dienstleistungen (B) und Information (D), die im Jahr 2003 mit 18 Unternehmen in den Top 25 vertreten waren. Die Spitzenfunktion hält mit „yahoo!“ ein so genannter Multiple Content Provider, dessen Paid Content-Angebot sich über mehr als eine Produktkategorie erstreckt. Die geringe Anzahl an Multiple Content Providern in dieser Rangliste legt jedoch die Vermutung nahe, dass dieser Teilmarkt nur wenige Anbieter zulässt. Seit 2002 ist kein Unternehmen der Kategorie Forschung mehr in den Top 25 vertreten. Die genaue Verteilung der Paid Content-Anbieter auf Kategorien sowie der durchschnittliche Rang ist in Tabelle 4 dargestellt.

Tabelle 4. Entwicklung der Paid Content-Kategorien in den USA.

| Kategorie | 2001 | | 2002 | | 2003 | |
|------------------------------|----------------------------|-------------------------|----------------------------|-------------------------|----------------------------|-------------------------|
| | Anzahl an Top 25 Anbietern | Durchschnittlicher Rang | Anzahl an Top 25 Anbietern | Durchschnittlicher Rang | Anzahl an Top 25 Anbietern | Durchschnittlicher Rang |
| Multiple Content Provider | 2 | 9,5 | 2 | 9,5 | 2 | 10,5 |
| Persönliche Dienstleistungen | 7 | 8,7 | 8 | 9,9 | 9 | 9,1 |
| Entertainment | 4 | 13,6 | 5 | 15 | 5 | 13 |
| Information | 11 | 15,4 | 10 | 15,2 | 9 | 17,4 |
| Forschung | 1 | 23 | 0 | 0 | 0 | 0 |
| Summe | 25 | 13 | 25 | 13 | 25 | 13 |

Für Europa zeichnen aktuelle Untersuchungen ein ähnliches Bild bezüglich des Wachstums, das Marktvolumen ist jedoch deutlich niedriger. Auf die einzelnen Länder heruntergebrochen besitzt Deutschland den größten Anteil mit einem Umsatz von 14 Millionen Euro im Jahre 2002 sowie einem erwarteten jährlichen Wachstum um 110% auf 127 Millionen im Jahr 2005 (Oelbermann und v. Reibnitz 2003; Stahl und Siegel 2004). Der Anteil an deutschen Internetnutzern, die bereits digitale Produktkäufe online abgewickelt haben, liegt mit 56% sogar weit über der Vergleichszahl des nordamerikanischen Marktes (Oehmichen und Schöter 2003).

Basierend auf einer Befragung von Onlinenutzern im Rahmen der ARD/ZDF-Online-Studien 2004 und 2005 zur Nutzung kostenpflichtiger Inhalte im Internet, kann auf eine Dominanz von Angeboten der Kategorie Information im deutschen Paid Content-Markt geschlossen werden. Eine wachsende Bedeutung besitzen außerdem, getrieben durch die stark steigende Nachfrage nach kostenpflichtigen Musikfiles, Angebote aus der Kategorie Entertainment. Persönliche Dienstleistungen, Forschung und Angebote von Multiple Content Provider werden kaum nachgefragt (v. Eimeren und Frees 2005).

Um eine genauere Betrachtung des Marktes für digitale Produkte in Deutschland vornehmen zu können, wurde im Rahmen einer Befragung die derzeitige und zukünftige

Marktentwicklung sowie das Konsumentenverhalten durch Paid Content-Manager analysiert. Die Erhebung wurde im Wesentlichen auf zwei Messen in Deutschland („CeBIT“ und „Buchmesse Leipzig“) im Jahr 2004 durchgeführt. Insgesamt wurden den 20 teilnehmenden Paid Content-Managern 32 Fragen zu den Komponenten des strategischen Dreiecks (Unternehmen, Wettbewerber, Konsumenten) sowie den Instrumenten des Marketing-Mix (Produkt, Preis, Distribution, Promotion) gestellt. Jede Kategorie digitaler Produkte (Multiple Content Provider, Entertainment, Information, Persönliche Dienstleistungen, Forschung) war mit mindestens zwei Managern vertreten.

Die befragten Manager sehen den Paid Content-Markt weiterhin als Wachstumsmarkt. Während 65% der Befragten von einem kontinuierlichen Wachstum innerhalb der nächsten fünf Jahre ausgehen, sind 35% sogar von einem sehr starken Marktwachstum überzeugt. 90% der Befragten sehen dabei die immer stärkere Transformation von kostenfreien Inhalten zu Paid Content durch bestehende Anbieter digitaler Produkte als wichtigsten Faktor für das Marktwachstum und die Kundenakzeptanz an. 60% der Manager erscheint ein gemischtes Erlösmodell (transaktions- und werbebasiert) und 40% ein rein transaktionsbasiertes Erlösmodell erfolgsversprechend für den Handel mit digitalen Produkten. Keiner der befragten Manager sieht in seinem Markt langfristig eine Chance für rein werbefinanzierte Angebote. Das größte Wachstum innerhalb des Gesamtmarktes für digitale Produkte wird in den bereits dominierend Kategorien Information (+40%) und Entertainment (+35%) erwartet. Das Wachstumspotential der Märkte für Multiple Content (+10%), Persönliche Dienstleistungen (+10%) und Forschung (+5%) wird dagegen eher als gering eingeschätzt.

Bei einem Vergleich des US-amerikanischen mit dem deutschen Markt wird vor allem die unterschiedliche Beurteilung und Entwicklung der Kategorie „persönliche Dienstleistungen“ deutlich. Während entsprechende Produktangebote in Deutschland nur in geringem Umfang vorzufinden sind und auch die zukünftige Entwicklung nur als bedingt erfolgsversprechend angesehen wird, hat diese Kategorie in den USA eine ganz andere Entwicklung genommen. Persönliche Dienstleistungen sind dort gegenwärtig bereits ein wichtiger Faktor. Im Jahr 2003 waren bereits 9 der 25 erfolgreichsten Anbieter von Paid Content im US-amerikanischen Markt Anbieter persönlicher Dienstleistungen, mit steigender Tendenz (siehe Tabelle 4).

2.3. Überblick über die Akzeptanz von Paid Content-Angeboten

Während sich Paid Content-Angebote im B2B-Bereich schon seit längerem etabliert haben (z.B. zahlen Universitäten und Unternehmen für den Zugang zu Datenbanken wie elektronischen Bibliotheken, Unternehmens- und Finanzanalysen), ist der Paid Content-Markt im B2C-Bereich zurzeit noch als eher klein und wenig entwickelt zu bezeichnen. Das Anbieten kostenfreier Informationen in der Entstehung und weiteren Entwicklung des Internets hat bei vielen Konsumenten zur Ausbildung einer „for free“ Mentalität geführt (PricewaterhouseCoopers 2004). Nicht zuletzt aufgrund dieser Mentalität wurden im Jahr 2004 lediglich auf 3% der umsatzgenerierenden Webseiten überhaupt digitale Produkte zum Verkauf angeboten (BVDM 2004). Die Existenz dieser „for free“ Mentalität wird unter anderem in einer Studie von RampRate und Synovate (RampRate 2003) aus dem Jahre 2003 deutlich, in der 68% der Internetnutzer in den USA nicht bereit waren, für das Streaming von Audio- und Videodateien zu bezahlen. Fast die Hälfte (47,5%) aller Befragten waren der Meinung, dass alle Angebote im Internet kostenlos zur Verfügung gestellt werden sollten und 20% sehen kostenpflichtige digitale Produkte als Grund zur Beendigung des „Surfens“ im Internet. Dementsprechend erfreuen sich kostenfrei erhältliche Produkte auf Webseiten oder in Peer-to-Peer Netzwerken auch nach einigen Gerichtsurteilen gegen Betreiber und Content-Provider weiterhin großer Beliebtheit (Boumans 2004). Weitere Gründe für die geringe Zahlungsbereitschaft liegen neben der bestehenden „for free“ Mentalität und der großen Verfügbarkeit kostenloser Produktangebote im Internet in den neuen und teilweise komplizierten Abrechnungs- und Bezahlverfahren, der Angst vor Sicherheitsrisiken bei der Bezahlung mit der Kreditkarte und dem Schutz der Privatsphäre (Oelbermann und v. Reibnitz 2003).

Neue Marktanalysen zeigen jedoch, dass die Akzeptanz für den käuflichen Erwerb digitaler Produkte speziell bei Internetnutzern mit Breitbandzugang steigt (Boumans 2004; Stern 2005). Die Entwicklung der Zahlungsbereitschaft für Paid Content hängt hierbei stark von dem betroffenen Produkt ab. Während für kostenpflichtige Inhalte wie interaktive Filme, Multimedia-Messages und Video-Spiele in den nächsten Jahren ein starker Anstieg der Nachfrage zu erwarten ist (PricewaterhouseCoopers 2004), erfahren beispielsweise Zeitungen und Zeitschriften, die ihre Produkte nur noch gegen eine Gebühr online zur Nutzung freigeben, ein dramatisches Absinken der Besuchszahlen (Boumans 2004).

Zusammenfassend kann festgestellt werden, dass der Markt für Paid Content seit dem Jahr 2001 ein starkes Wachstum verzeichnen kann. Dieses Wachstum wird getrieben durch die

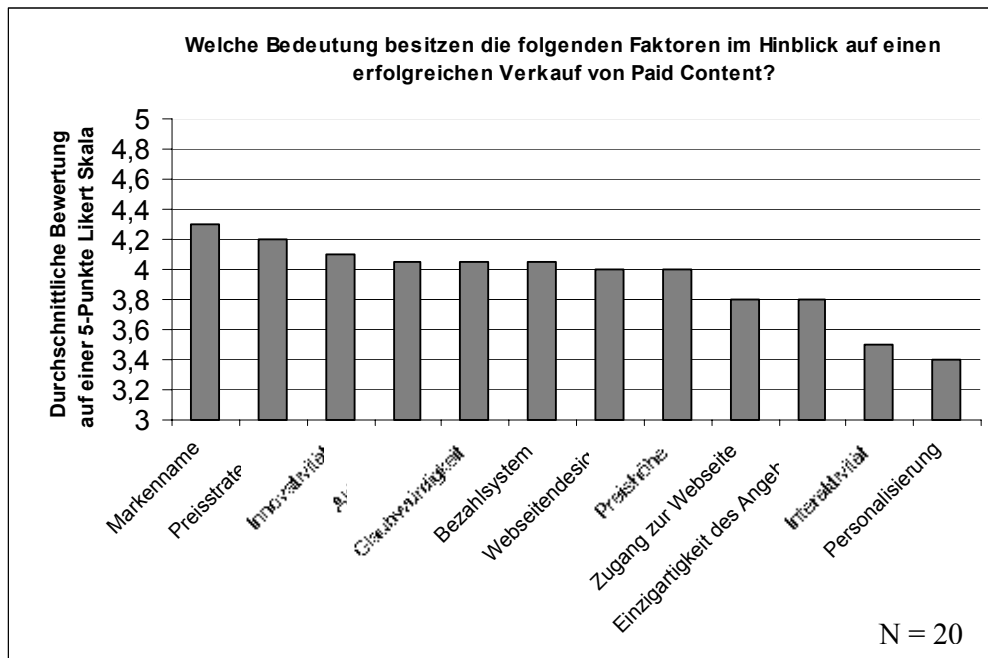
Notwendigkeit der Implementierung von transaktionsbasierten Erlösmodellen auf Seiten der Unternehmen sowie der schnellen Verbreitung von Breitbandzugängen für das Internet. Die Gruppe der Konsumenten mit einer Zahlungsbereitschaft für Paid Content wächst, variiert aber sehr stark zwischen Internetnutzern und Produktangeboten. Hieraus ergeben sich spezielle Anforderungen an die Preispolitik der Unternehmen, da große Unterschiede in der Zahlungsbereitschaft die Optimierung der Preisgestaltung zur Steigerung des Gewinns bei den veränderten Produktions- und Vertriebsbedingungen für digitale Produkte erschweren.

3. Preisdifferenzierung im Paid Content-Markt

3.1. Bedeutung der Preispolitik

Die besondere Bedeutung der Preissetzung zeigt sich in der Einschätzung von Erfolgsfaktoren für den Verkauf digitaler Produkte durch Paid Content-Manager. Bei der Bewertung auf einer 5-Punkte Likert Skala wird die Preisstrategie neben dem Markennamen des Unternehmens beziehungsweise des Produkts von den Probanden hervorgehoben (siehe Abbildung 1).

Abbildung 1. Bedeutung von Erfolgsfaktoren für Paid Content.



Die befragten Paid Content-Manager sehen im Bereich Preis (35%) mit das größte Potential zur Steigerung des Paid Content-Geschäfts und der Forschungsbedarf wird im Bereich Preispolitik mit 45% der Nennungen aufgrund der schon beschriebenen „for free“ Mentalität,

der Anwendbarkeit komplizierter Preismodelle (z.B. Auktionen, Reverse Pricing) sowie der Möglichkeit zur zeitlich sehr schnellen Veränderung oder Anpassung von Preisen, am Größten eingeschätzt.

Passend zu dem geäußerten Forschungsbedarf im Bereich Preispolitik stellt sich die Situation bei der Anwendung von Preissetzungsverfahren dar. Hier dominiert neben der Orientierung an Wettbewerbspreisen das „trial & error“ Prinzip, das heißt Unternehmen setzen und verändern Preise aus dem Bauchgefühl heraus. Des Weiteren gaben 70% der befragten Entscheidungsträger an, verschiedene Strategien der Preisdifferenzierung für die angebotenen digitalen Produkte einzusetzen. Als besonders häufig angewandte Formen der Preisdifferenzierung wurden insbesondere der Mengenrabatt (40%) und das Versioning (15%) genannt. Das beliebteste Preismodell zur Umsetzung der Preisdifferenzierung im deutschen Paid Content-Markt ist laut Managern ein zweiteiliger Tarif (Grundpreis + Pay-Per-Use) (45%), gefolgt von Pay-Per-Use Tarifen (30%) und Pauschaltarifen (Flat-Rate (25%).

3.2. Formen der Preisdifferenzierung

Die Idee der Preisdifferenzierung besteht darin, ein prinzipiell gleiches Produkt an verschiedene Nachfrager zu unterschiedlichen Preisen möglichst gewinnbringend zu verkaufen (Skiera 2001). Dies impliziert, dass Konsumenten unterschiedliche Zahlungsbereitschaften für das gleiche Produkt besitzen (Shapiro und Varian 1998; Whinston et al. 1997). Bedingung für die erfolgreiche Umsetzung von Preisdifferenzierungsstrategien ist die Trennbarkeit von Märkten sowie die Vermeidung von Arbitragemöglichkeiten. Sind diese Voraussetzungen erfüllt, kann mittels Preisdifferenzierung insbesondere unter Annahme geringer variabler Produktkosten eine Steigerung des Gewinns erzielt werden.

Der Einsatz der Preisdifferenzierung im Paid Content-Markt erscheint insbesondere durch die in Kapitel 2.3 beschriebenen Unterschiede in den Zahlungsbereitschaften von Paid Content-Konsumenten sowie den, verglichen mit physischen Produkten, verbesserten Möglichkeiten zur Abgrenzung von Märkten vorteilhaft. Zu diesen verbesserten Möglichkeiten der Abgrenzung von Märkten zählen unter anderem die direkte Abfrage und Speicherung von Konsumenteninformationen auf der Webseite des Unternehmens (z.B. durch einen personalisierten Zugang), die verbesserten Möglichkeiten des Informationszukaufs von Datensammelstellen (z.B. ATPCO), die Beobachtung von Konsumentenverhalten (z.B. durch das Platzieren von Cookies auf dem Rechner der Konsumenten), die direkte

Konsumentenansprache (z.B. personalisiertes Angebot) und die Individualisierung des endgültigen Produktpreises (z.B. durch das Einräumen von Preisnachlässen).

Es können zwei wesentliche Gestaltungsformen der Preisdifferenzierung unterschieden werden (Skiera 2001). Bei der Preisdifferenzierung ohne Selbstselektion wird für einzelne Konsumenten oder Gruppen von Konsumenten ein individueller oder gruppenbezogener Preis festgelegt (z.B. Student, Rentner), bei der Preisdifferenzierung mit Selbstselektion werden den Konsumenten mehrere Produktvarianten zu verschiedenen Preisen angeboten. Hierdurch kann die bei der Preisdifferenzierung ohne Selbstselektion anfallende Kontrolle der Zugehörigkeit der einzelnen Konsumenten zu einer Gruppe durch den Produkthanbieter vermieden werden (siehe Tabelle 5).

Tabelle 5. Möglichkeiten der Preisdifferenzierung.

| Möglichkeiten der Preisdifferenzierung | | | | |
|--|----------------------------|--------------|--|-------------------------------------|
| Ohne Selbstselektion (Segmentierung) | | | Mit Selbstselektion | |
| Individuelle Festlegung | Gruppenbezogene Festlegung | Zeit-bezogen | Mengen-bezogen (z.B. Mengenrabatte, Preisbündelung, Tarifwahl) | Leistungs-bezogen (z.B. Versioning) |

(Quelle: Skiera 2001)

Basierend auf einer Webseitenanalyse zur Identifikation von Erfolgsfaktoren für Paid Content werden im Folgenden die von 118 Paid Content-Anbietern aus den USA und Deutschland zurzeit am häufigsten verwendeten Formen der Preisdifferenzierung für Paid Content vorgestellt und diskutiert. Dabei kann zwischen den in Tabelle 6 dargestellten Formen unterschieden werden:

Tabelle 6. Formen der Preisdifferenzierung.

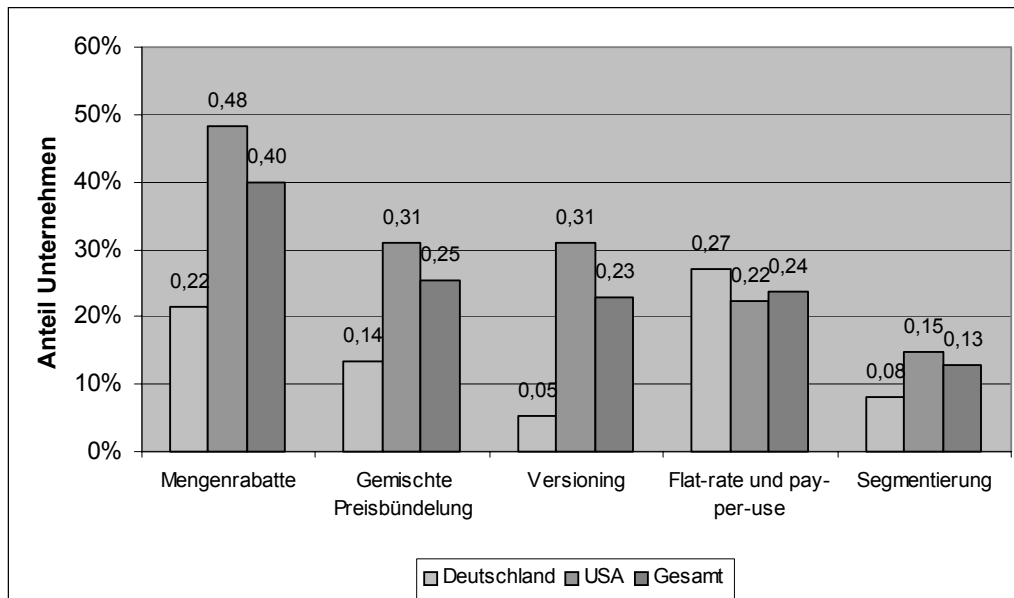
| Form der Preisdifferenzierung: | Beschreibung |
|--------------------------------|---|
| Mengenrabatt | Steigende Kaufmengen führen zu einem sinkenden Preis pro Produkteinheit (mit Selbstselektion) |
| Preisbündelung | Produkte werden sowohl einzeln als auch in Kombination mit anderen Produkten angeboten (mit Selbstselektion) |
| Versioning | Produktvarianten werden in unterschiedlicher Qualität zu unterschiedlichen Preisen angeboten (mit Selbstselektion) |
| Tarifwahl | Anbieten eines Produkts in Verbindung mit unterschiedlichen Tarifen (z.B. Flat-Rate, Pay-Per-Use) (mit Selbstselektion) |
| Segmentierung | Abgrenzung von Konsumentengruppen anhand gruppenspezifischer Konsumentencharakteristika (ohne Selbstselektion) |

Die Stichprobe ist unterteilt in 37 Webauftritte deutscher Paid Content-Anbieter (in deutscher Sprache) sowie 81 Webauftritte von US-amerikanischen Paid Content-Anbietern (in englischer Sprache). Die beschriebenen Produktkategorien im Paid Content-Markt sind wie

folgt vertreten: 36 Anbieter von persönlichen Dienstleistungen, 32 Anbieter von digitalen Entertainment Produkten, 39 Anbieter von Informationsprodukten, 9 Anbieter aus der Kategorie Forschung und 2 Multiple Content Anbieter. Neben den 25 führenden Paid Content-Anbietern aus dem US-amerikanischen Markt (Online Publishers Association 2004) wurden Anbieter ausgewählt, die in einer der Paid Content-Marktstudien der Online Publishers Association und VDZ/Sapient oder in Artikeln über digitale Produkte aus der LexisNexis Datenbank aufgeführt wurden. Die Beurteilung der Webseiten bezüglich der Anwendung von Formen der Preisdifferenzierung wurde in separaten Bewertungsrunden von drei Personen vorgenommen.

Bei einer gemeinsamen Betrachtung beider Märkte (siehe Abbildung 2) lässt sich erkennen, dass die fünf untersuchten Formen der Preisdifferenzierung regelmäßig von Paid Content-Anbietern eingesetzt werden. Im Durchschnitt wendet ein Paid Content-Unternehmen mehr als eine Form (1,25) der Preisdifferenzierung an. Am häufigsten sind Mengenrabatte (40%) zu beobachten. Eine Begründung hierfür könnte die weite Verbreitung von Mengenrabatten beim Handel mit physischen Produkten sein (Dolan 1987). Nason und Della Bitta (1983) konnten sogar zeigen, dass Konsumenten einen Mengenrabatt erwarten (Nason und Della Bitta 1983). Jeder vierte der untersuchten Anbieter von digitalen Produkten bietet seine Produkte sowohl einzeln als auch in Produktbündeln an. Da der Einsatz der Preisbündelung im Falle niedriger variabler Produktionskosten höhere Gewinne verspricht, erscheint diese Strategie speziell für digitale Produkte vorteilhaft (Olderog und Skiera 2000). Auch die Strategie des Versionings von Informationsprodukten wird von fast einem Viertel (23%) der Paid Content-Anbieter angewendet. Dies bestätigt die Aussage, dass aufgrund der einfachen und kostengünstigen Möglichkeit der Reproduktion und Veränderung digitaler Produkte Versioning im Internet besondere Möglichkeiten zur Steigerung der Gewinne bietet (Shapiro und Varian 1998). Das Anbieten von mehreren Tarifen (letztlich eine optionale mengenbezogene Preisdifferenzierung) ist durch die vereinfachte Umsetzung und Abrechnung über digitale Netzwerke ebenfalls häufig zu beobachten (24%).

Abbildung 2. Vergleich der Preisdifferenzierung in den USA und Deutschland.



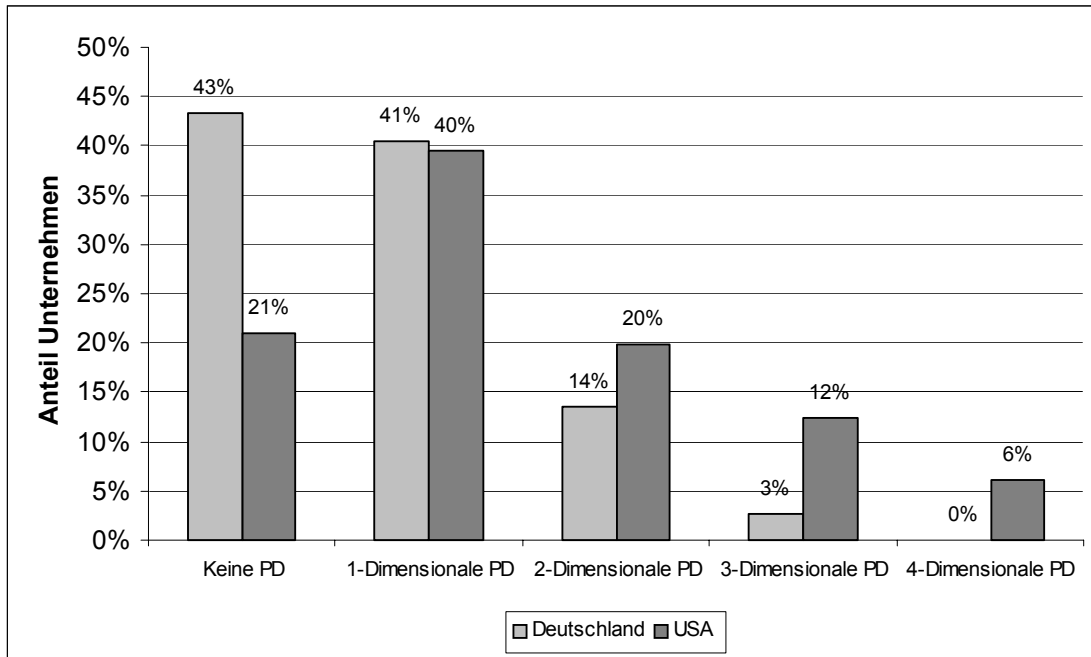
Während also die untersuchten Formen der Preisdifferenzierung mit Selbstselektion vielfach auftreten, ist die Segmentierung als Form der Preisdifferenzierung ohne Selbstselektion eher selten (13%). Dies ist wenig überraschend, da für die Preisdifferenzierung ohne Selbstselektion in der Regel ein persönlicher Kontakt zur Überprüfung von Segmentierungskriterien erforderlich ist. In einem anonymen Netzwerk wie dem Internet scheint die Selbstselektion durch den Nutzer größeren Erfolg zu versprechen (siehe Tabelle 6).

Bei einem Vergleich der Anwendungshäufigkeit zwischen dem US-amerikanischen und dem deutschen Paid Content-Markt fällt auf, dass in den USA 79% aller Anbieter von Paid Content eine Form der Preisdifferenzierung vornehmen, wohingegen es in Deutschland nur 57% sind. Von den fünf beschriebenen Formen der Preisdifferenzierung werden von Paid Content-Anbietern in Deutschland lediglich die Tarifwahl (27%) und Mengenrabatte (22%) relativ häufig eingesetzt.

Verglichen mit physischen Produkten können verschiedene Formen der Preisdifferenzierung (z.B. Versioning, Preisbündelung) aufgrund der Digitalisierung relativ schnell und kostengünstig umgesetzt werden. Die Verknüpfung mehrerer Formen der Preisdifferenzierung stellt somit für Paid Content-Anbieter ein realistisches und aufgrund des daraus möglichen höheren Differenzierungsgrades ein erfolgsversprechendes Konzept zur Steigerung des Gesamtdeckungsbeitrags dar. Bei der Anwendung mehrdimensionaler Preisdifferenzierung ist für Unternehmen darauf zu achten, dass nicht durch eine zu komplexe Preisstruktur

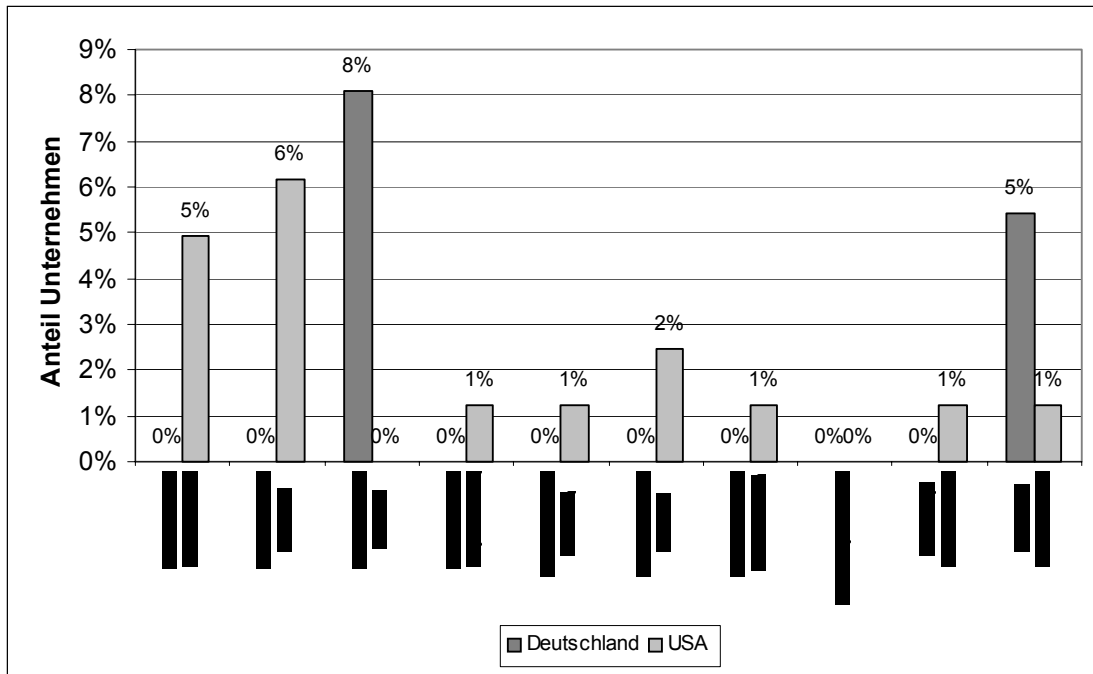
potenzielle Kunden von einem Kauf abschreckt werden (Skiera und Spann 2000). Große Unterschiede bestehen auch hier zwischen dem US-amerikanischen und dem deutschen Paid Content-Markt. Während in beiden Ländern eine vergleichbare Anzahl an Unternehmen eine eindimensionale Preisdifferenzierung wählt, ist die Anwendung mehrdimensionaler Preisdifferenzierung in den USA wesentlich populärer (siehe Abbildung 3).

Abbildung 3. Überblick über die Anwendung der mehrdimensionalen Preisdifferenzierung (PD) im Paid Content-Markt in den USA und Deutschland.



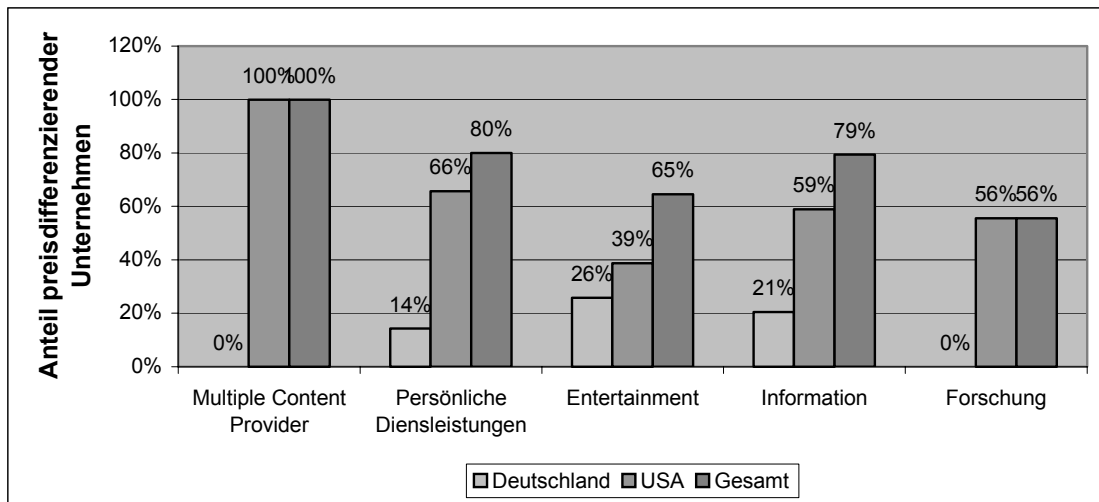
Anbieter von Paid Content in Deutschland wählen bei der Umsetzung einer 2-dimensionalen Preisdifferenzierung in der Regel eine Kombination aus Tarifwahl und Mengenrabatt oder Segmentierung. Im US-amerikanischen Markt gibt es keine eindeutige Tendenz. Fast jede Kombination der fünf untersuchten Formen der Preisdifferenzierung ist vertreten, am häufigsten werden Mengenrabatte mit Versioning oder Preisbündelung verknüpft (siehe Abbildung 4).

Abbildung 4. Überblick über die Anwendung der 2-dimensionalen Preisdifferenzierung im Paid Content-Markt in den USA und Deutschland.



Bei einem Vergleich der Anwendung von Preisdifferenzierung zwischen den Produktkategorien im Paid Content-Markt (siehe Abbildung 5) kann außerdem festgestellt werden, dass Unternehmen von den in Abschnitt 2.2 beschriebenen erfolgreichsten Produktkategorien im US-amerikanischen Markt (persönliche Dienstleistungen und Information) prozentual am häufigsten mindestens eine der beschriebenen Formen der Preisdifferenzierung einsetzen (die geringe Anzahl an Multiple Content Provider in der Untersuchung lässt eine Interpretation der prozentualen Anwendung für diese Kategorie nicht zu).

Abbildung 5. Überblick über die Anwendung der Preisdifferenzierung in den fünf Paid Content-Produktkategorien.



4. Zusammenfassung

Die Bedeutung von transaktionsbasierten Erlösmodellen für digitale Produkte nimmt seit dem Jahr 2001 stark zu. Der Paid Content-Markt im B2C-Bereich verzeichnet sowohl in Deutschland als auch in den USA hohe Wachstumsraten und Entscheidungsträger involvierter Unternehmen sehen in der nahen Zukunft keine Veränderung dieses Trends. Die bedeutendsten Produktkategorien im US-amerikanischen Paid Content-Markt sind „Information“ und „persönliche Dienstleistungen“, im deutschen Paid Content-Markt sind dies „Information“ und „Entertainment“. Der US-amerikanische Paid Content-Markt besitzt zurzeit ein wesentlich größeres Marktvolumen als sein deutsches Pendant. Die Spannweite der Zahlungsbereitschaft für digitale Produkte reicht unter den Internetnutzern in beiden betrachteten Märkten von nicht vorhanden bis hoch. Insbesondere Breitbandnutzer sind immer häufiger bereit, für digitale Güter und Serviceleistungen zu bezahlen.

Die Preisdifferenzierung stellt aufgrund der Unterschiede in den Zahlungsbereitschaften der Konsumenten und der mit digitalen Produkten und Netzen verbundenen einfachen technischen Umsetzung verschiedener Formen der Preisdifferenzierung eine erfolgsversprechende Preisstrategie dar. Bei einer Untersuchung von Anwendungsformen der Preisdifferenzierung im Internet konnte festgestellt werden, dass die Mehrzahl der am Markt befindlichen Unternehmen diese Strategie zur Steigerung des Gesamtdeckungsbeitrags bereits verfolgen. Dies trifft insbesondere für den US-amerikanischen Markt zu, da dort ein Paid Content-Anbieter im Durchschnitt mehr als eine Form der Preisdifferenzierung

vornimmt. Die Preisdifferenzierung mit Selbstselektion wird über beide Märkte hinweg der Preisdifferenzierung ohne Selbstselektion vorgezogen. Aufgrund der vergleichsweise einfachen Umsetzung verschiedener Formen der Preisdifferenzierung erscheint auch das Anbieten nach mehreren Dimensionen differenzierter Preise zur feineren Segmentierung des Marktes interessant. Auch hier ist bereits eine relative häufige Anwendung in den USA zu beobachten. Deutsche Paid Content-Anbieter sind zurzeit eher zurückhaltend und verwenden lediglich Kombinationen aus Tarifwahl und Mengenrabatt oder Tarifwahl und Segmentierung. Trotz der Erhöhung der Komplexität durch den Einsatz mehrdimensionaler Preisdifferenzierung und der damit verbundenen Abschreckung potenzieller Konsumenten könnten durch die Wahl eines einfachen und verständlichen Tarifs wie der Flat-Rate und dem Pay-Per-Use eine Überforderung des Konsumenten vermieden werden.

Die vorliegende Analyse des Paid Content-Marktes in Deutschland und den USA bestätigt das große Wachstumspotential für Paid Content. Sie zeigt jedoch auch Unterschiede bezüglich des Marktvolumens und der Preispolitik zwischen diesen beiden Märkten. Sowohl die Marktgröße des US-amerikanischen Paid Content-Marktes, als auch die Einnahmen der US-amerikanischen Paid Content-Anbieter und die große Anzahl an preisdifferenzierenden Unternehmen in den erfolgreichsten Produktkategorien (persönliche Dienstleistungen und Information) deuten auf einen engen Zusammenhang zwischen der Anwendung von Preisdifferenzierung und einem erfolgreichen Verkauf digitaler Produkte hin. Während Paid Content-Anbieter in den USA bereits vermehrt verschiedene Formen der ein- und mehrdimensionalen Preisdifferenzierung einsetzen und somit versuchen, sich den sehr unterschiedlichen Zahlungsbereitschaften der Internetnutzer anzupassen, ist die Anwendung der Preisdifferenzierung im deutschen Paid Content-Markt bis heute vergleichsweise gering.

Literaturverzeichnis

- Boumans, J. (2004). Paid Content: E-Content Report 2. In Z. Karszen (Ed.), *ACTeN Anticipating Content Technology Needs* (pp. 1-22). URL: http://www.acten.net/uploads/images/374/IR-Paid_content-v7.pdf (Abruf: 20.03.2005).
- BVDM. (2004). *Kommerzielle deutsche Webseiten 2004*. URL: http://www.bvdw.org/de/data/pdf/studie_06.pdf (Abruf: 04.11.2005).
- Dolan, R. J. (1987). Quantity Discounts: Managerial Issues and Research Opportunities. *Marketing Science*, 6(1), 1-23.
- Geng, X., Stinchcombe, M. B., & Whinston, A. B. (2005). Bundling Information Goods of Decreasing Value. *Management Science*, 51(4), 662-667.
- Hitt, L. M., & Chen, P. (2005). Bundling with Customer Self-Selection: A Simple Approach to Bundling Low-Marginal-Cost Goods. *Management Science*, 51(10), 1481-1493.
- Lambrecht, A., & Skiera, B. (2006). Paying Too Much and Being Happy About It: Causes and Consequences of Tariff-Choice Biases. *Journal of Marketing Research*, 43(2), 212-223.
- Nason, R. W., & Della Bitta, A. J. (1983). The Incidence and Consumers Perceptions of Quantity Surcharges. *Journal of Retailing*, 59(2), 40-55.
- Oehmichen, E., & Schöter, C. (2003). Veränderungen des Mediennutzungsverhaltens bei Onlinenutzern - Funktionswandel der Massenmedien durch das Internet? *Media Perspektiven*, 8, 374-384.
- Oelbermann, M., & v. Reibnitz, A. (2003). *Paid Content - Der Markt für Online Inhalte*. Berlin.
- Online Publishers Association. (2003). *OPA Report: Paid Online Content U.S. Market Spending Report, Q4, FY 2002*. URL: http://www.online-publishers.org/pdf/opa_paid_content_report_mar03.pdf (Abruf: 18.02.2005).
- Online Publishers Association. (2004). *OPA Report: Paid Online Content U.S. Market Spending Report, FY 2003*. URL: http://www.online-publishers.org/pdf/opa_paid_content_report_may04.pdf (Abruf: 14.06.2005).
- Online Publishers Association. (2005). *Online Paid Content. In: U.S. Market Spending Report - FY2004*. URL: http://www.online-publishers.org/pdf/opa_paid_content_report_may04.pdf (Abruf: 02.11.2005).

- Point Topic. (2005). *World Broadband Statistics - Q2 2005*. URL: <http://www.point-topic.com/contentDownload/dslanalysis/world%20broadband%20statistics%20q2%202005.pdf> (Abruf: 05.11.2005).
- PricewaterhouseCoopers. (2004). *The Broadband Future - Interactive, Networked, and Personalised*. URL: <http://www.pwc.com/techforecast/pdfs/BBFutureUK.pdf> (Abruf: 05.11.2005).
- RampRate. (2003). Users Still Resistant to Paid Content. *Clickz Stats*, URL: <http://www.clickz.com/stats/sectors/retailing/article.php/2189551> (Abruf: 23.03.2005).
- Shapiro, C., & Varian, H. R. (1998). *Information Rules. A Strategic Guide to the Network Economy*. Boston: Harvard Business School Press.
- Shapiro, C., & Varian, H. R. (1998). Versioning: The Smart Way to Sell Information. *Harvard Business Review*, 76(6), 106-114.
- Skiera, B. (2001). Preisdifferenzierung. In S. Albers & M. Clement & K. Peters & B. Skiera (Eds.), *Marketing mit Interaktiven Medien. Strategien zum Markterfolg*. Frankfurt.
- Skiera, B., & Spann, M. (2000). Flexible Preisgestaltung im Electronic Business. In W. R. (Ed.), *Handbuch Electronic Business*. Wiesbaden.
- Skiera, B., Spann, M., & Walz, U. (2005). Erlösquellen und Preismodelle für den Business-to-Consumer-Bereich im Internet. *Wirtschaftsinformatik*, 47, 285-294.
- Stahl, F., & Siegel, F. (2004). *Paid Content - Paid Services, Analyse des deutschen Marktes und der Erfolgsfaktoren von 280 Geschäftsmodellen*. St. Gallen.
- Stern. (2005). Akzeptanz von Paid Content im Internet steigt. (URL: <http://www.stern.de/presse/stern/:19.10.2005-Akzeptanz-Paid-Content-Internet-/548009.html> (Abruf: 03.11.2005)).
- Sundararajan, A. (2004). Nonlinear Pricing of Information Goods. *Management Science*, 50(12), 1660-1673.
- v. Eimeren, B., & Rees, B. (2005). Nach dem Boom: Größter Zuwachs in internetfernen Gruppen. *Media Perspektiven*, 8, 362-379.
- v. Reibnitz, A., & Rautenberg, A. (2003). *Pricing von Paid Content und Paid Services*. Berlin.
- Whinston, A. B., Stahl, D. O., & Choi, S.-Y. (1997). *The Economics of Electronic Commerce*. Indianapolis: Macmillan Technical Publishing.

Multi-Channel Pricing Strategy: To Price Differentiate or Not

Agnieszka Wolk

Wolk, A. (2007). Multi-Channel Pricing Strategy: To Price Differentiate or Not. Working Paper, University of Frankfurt.

Multi-Channel Pricing Strategy: To Price Differentiate or Not

Abstract

Price differentiation has long been recognized as a strategy that companies can use to increase profits when consumers' tastes differ in terms of their valuations for a product. Operating multiple channels that have varying degrees of functionality and are differently valued by consumers (e.g., offline and online store) gives an opportunity for applying differential prices across them. In this paper, I study channel-based price differentiation and empirically analyze the extent of its occurrence among multi-channel retailers. Additionally, I analyze factors that influence a company's decision to engage in channel-based price differentiation in terms of probability of charging differential prices across channels as well as the size of the price differences. The results show that multi-channel retailers increasingly engage in channel-based price differentiation which contradicts price dispersion literature stream. However, current practices may be partly suboptimal for the retailers. Consistent with microeconomic theories the degree of price differentiation increases for big companies with market power that can separate markets.

Keywords: price differentiation, distribution channels, multi-channel pricing.

1. Introduction

Research in marketing and economics has long acknowledged that price differentiation can be a profitable pricing strategy (Montgomery 1997; Philips 1989). In the market of heterogeneous tastes and different product valuations, companies may increase their profits by segmenting consumers and charging them differential prices which allows for extracting additional consumer surplus. Empirical studies show that profit may increase by up to 34% when companies engage in price differentiation compared to a uniform pricing strategy (Khan and Jain 2005). As a result, researchers advocate using price differentiation (Philips 1989).

Among various forms, self-selection price differentiation has received special attention from researchers and practitioners due to its numerous advantages in terms of cost and easiness of application as well as profitability (Khan and Jain 2005; Philips 1989). In the case of self-selection price differentiation a company offers multiple product versions at various prices and allows consumers to choose the one that best suits their preferences (Mussa and Rosen 1978; Philips 1989).

Whereas various forms of self-selection price differentiation have been widely used by companies (e.g., versioning, coupons, damaged goods), technological developments constantly offer new application opportunities that may help to increase the profits. The growing popularity of the Internet has led many conventional retailers to initiate online sales and turn themselves into multi-channel retailers that offer their consumers a possibility to choose between online and offline distribution channels when conducting a purchase (Frazier 1999; Zettelmeyer 2000). Since online and offline channels differ on such aspects as, among others, convenience, risk or transparency (Chiang and Dholakia 2003), consumers develop heterogeneous channel preferences leading to differential channel valuations (Chu et al. 2007; Kacen et al. 2003). As a result, operating multiple channels gives an opportunity for applying channel-based price differentiation where companies can charge different prices for the same product in online and offline channel and allow consumers to self-select into the preferred channel-price combination.

While theoretical work acknowledges such a possibility and accounts for that in analytical models (Dulleck and Kerschbamer 2005; Dzienziol et al. 2002; Zettelmeyer 2000), recent empirical studies fail to find evidence for channel-based price differentiation (e.g., Ancarani and Shankar 2004; Pan et al. 2002; Tang and Xing 2001). These results may be due to the

fact that existing studies focus on analyzing price dispersion in online and offline environment rather than price differentiation. Therefore, while good reasons exist in support of engaging in channel-based price differentiation, the research is needed to examine the extent to which companies apply that (Neslin et al. 2006).

Although price differentiation has been shown to increase the profits, not all multi-channel retailers are equally willing to follow this strategy. Therefore, another question about the company's motivation to engage in channel-based price differentiation emerges. Unfortunately, little research has focused on the question whether to price differentiate or not (Anderson and Dana 2006). While this topic received some attention in the theoretic economic literature (e.g., Anderson and Dana 2006; Salant 1989; Stokey 1979) where the authors develop analytical models to explain when companies engage in price differentiation, the empirical research in this area is very scarce. The only exception includes Iyer and Seetharaman (2001) who use survey data to analyze a limited number of factors that motivate gasoline stations to offer multiple products and engage in price differentiation.

Consequently, the aim of this study is to analyze the occurrence and a company's incentive to engage in a channel-based price differentiation. First, I analyze whether multi-channel retailers charge differential prices for the same product in online and offline channel and how big the differences are. Since not all retailers are equally willing to engage in channel-based price differentiation, in the second step I analyze empirically market-specific, company-specific and product-specific factors that influence the extent of price differentiation. Both the decision to engage in channel-based price differentiation as well as the size of the price differences are analyzed.

The reminder of the paper is organized as follows. First, I review the existing literature on channel-based price differentiation and multi-channel pricing. Next, I provide the rational for channel-based price differentiation and develop hypotheses regarding the factors that may influence the company's decision to engage in channel-based price differentiation. Then, I describe the data sets and present the results of two empirical studies. Lastly, the discussion of the results and concluding remarks come.

2. Literature review

Various studies have considered price differentiation in the context of a distribution channel. Jeuland and Shugan (1983) propose the usage of quantity discounts as a means to assure channel cooperation in the context of a single manufacturer-retailer distribution channel

while McGuire and Staelin (1983) and Moorthy (1987) propose two-part tariffs in this context. Gerstner et al. (1994) and Gerstner and Hess (1995) study price differentiation within a distribution channel when a manufacturer issues coupons that can be realized in the retailer as a means of channel coordination. The authors show that such a pull strategy can be a practical strategy that alleviates double marginalization and channel miscoordination. Besanko et al. (2003) analyze the manufacturer and retailer possibility of engaging in price differentiation by issuing segment-specific coupons to consumers in the context of a vertical channel.

While these studies focus on within channel price differentiation strategies, Iyer (1998) develops a theoretical model and analyzes a manufacturer selling through competing retailers that uses contracts to induce price-service differentiation among retailers. Also Dulleck and Kerschbamer (2005) analyze theoretically the application of different distribution channels in order to price differentiate along the quality of advice. The authors show in their analytical model that with heterogeneous consumers and market power manufacturer in equilibrium may sell through both expert outlets and warehouse outlets and charge differentiation prices between them. Dzienziol et al. (2002) go one step further and focus specifically on online and offline distribution channel for the financial services and recognize the possibility for channel-based price differentiation in this context. Similarly, Zettelmeyer (2000) who analyze pricing and communication strategies of multi-channel retailers accounts for the possibility for channel-based price differentiation in his theoretical model.

While the theoretical literature suggests the possibility of channel-based price differentiation, practitioners argue that in order to maintain a strong brand the company offer has to be consistent across distribution channels (Asheraft 2001; Del Franco and Chiger 2002). Varying prices may lead to customer confusion, anger, irritation and a perception of price unfairness (Asheraft 2001; Del Franco and Chiger 2002; Neslin et al. 2006). Since previous research has shown that unfair price perceptions decrease purchase intentions (e.g., Campbell 1999), practitioners advocate “channel price integrity”.

In a similar vein, existing studies analyzing empirically price dispersion in online and offline environments fail to acknowledge or find empirical evidence for channel-based price differentiation. Pan et al. (2002) in their approach follow the anecdotal evidence and make the assumption that in order to preserve channel integrity the multi-channel retailer sets the same price at its two stores. Ancarani and Shankar (2004) report that although prices for some multi-channel retailers were different across channels, on average the differences were

not significant and therefore, they proceed with their analysis assuming equal prices. Similarly, Tang and Xing (2001) argue that multi-channel retailers may wish to charge the same prices across their different channels to prevent destructive competition and conflict between them. Lastly, Sullivan and Thomas (2004) who analyze channel choice in multi-channel environment find consistent prices across channels in their data set leading to the conclusion that multi-channel retailers prefer to promote the uniformity of their channels than to engage in channel-based price differentiation.

This literature review leads to the conclusion that in theory channel-based price differentiation seems to be an appealing and feasible pricing strategy but existing empirical studies fail to find the evidence for companies following it.

Since not all companies have the same motivation to engage in price differentiation, the question emerges which companies follow this pricing strategy. Various studies analyze theoretically a company's motivation to engage in price differentiation and the conditions for profitable self-selection price differentiation (e.g., Anderson and Dana 2006; Deneckere and McAfee 1996; Salant 1989; Stokey 1979). For example, Anderson and Dana (2005) derive conditions for profitable price differentiation that generalize existing results in the literature and apply to various forms of self-selecting price differentiation (e.g., intertemporal price differentiation, coupons, versioning). The authors show that price differentiation is profitable if the ratio of the marginal social value from an increase in quality to the total social value of the good is increasing in consumers' willingness to pay (Anderson and Dana 2005).

However, the empirical research in this area is very scarce. Iyer and Seetharaman (2001) investigate such gasoline station incentives to price differentiate as income spread in the market, brand strength, presence of pay-at-pump facility or a convenience store. Based on survey data, Iyer and Seetharaman (2001) find that a larger income spread in the market implies a greater likelihood of a gasoline station being multi-product and thus exercising price differentiation. Additionally, branded stations with service stations but with no pay-at-pump facility and no convenience store are more likely to engage in price differentiation.

3. Conceptual model

Operating multiple channels opens a possibility to engage in channel-based price differentiation. Researchers show that price differentiation is advantageous for companies as it leads to increased profits (e.g., Chintagunta et al. 2003; Khan and Jain 2005; Leslie 2004; Montgomery 1997) and should therefore be used whenever possible (Philips 1989).

Nevertheless, various requirements have to be met so that the price differentiation is feasible. Below the conditions for successful application of price differentiation derived from the microeconomic theory are discussed. They include market, company and product characteristics.

3.1. Market characteristics

Consumer heterogeneity. Price differentiation is only feasible when consumers have heterogeneous preferences and varying willingness to pay that translate into varying price elasticities. With respect to online and offline distribution channels consumers have been shown to perceive channels differently with regard to convenience, risk, entertainment, search costs, face-to-face contact and transparency (Chiang and Dholakia 2003). As a result, consumers derive different utilities from various distribution channels and develop heterogeneous preferences for distribution channels (Chu et al. 2007). These differences lead, in turn, to different channel valuations and different willingness to pay for a product purchased in online and offline channels. Kacen et al. (2003) show that differences in willingness to pay for a product purchased in online channel compared to offline channel can be as high as 8% - 22% of the product price. Similarly, Jensen et al. (2003) find that consumers differ in their perceived prices between online and offline channel. Therefore, even though price dispersion literature implies uniform pricing across channels, hypothesis 1 proposes that channel-based price differentiation is feasible in a sense that there are multi-channel retailers that charge differential prices in online and offline channel.

H1. Channel-based price differentiation is feasible.

Price level across distribution channels. Differences in channel perceptions translate into differences in price sensitivities. Existing literature indicates that due to lower search cost for price information consumers will have a higher price sensitivity in online than in offline channel (Bakos 1997). Nevertheless, an online channel allows consumers to obtain more information not only about the price but also about non-price attributes, such as product quality (Alba et al. 1997). As a result, easier quality search may decrease price sensitivity and even outweigh the effect of easier price search (Alba et al. 1997; Lynch and Ariely 2000). Indeed, empirical studies support this notion. Lynch and Ariely (2000) show that in presence of both easy price and quality search price sensitivity is lower compared to the situation when both are difficult. As such, these results indicate lower price sensitivity online. Also results of Shankar et al. (2001) suggest that distinctive characteristics of online channel may decrease

price sensitivity in this channel. In a similar vein, Degeratu et al. (2000) show that the combined effect of price and price promotions on product choice is weaker online than offline.

Price differentiation requires that price levels are set depending on the price elasticity with higher elasticities being related to lower prices and lower elasticities being related to higher prices (i.e., inverse elasticity rule; Rao 1993). Taking into account existing research on price elasticities in online and offline channels, multi-channel retailers should charge higher prices in online channel than in offline channel.

H2. Multi-channel retailers that engage in channel-based price differentiation will charge higher prices for the same product in online than in offline channel.

Competition. Even when consumers have heterogeneous tastes, not all companies have the same incentive to engage in price differentiation. Microeconomic theory argues that a company must have a market power in a sense that it has the ability to set the price above the marginal cost to be able to charge differential prices (Philips 1989). In the purely competitive market where price equals marginal cost every company has to accept the same market price. Since any attempt to increase the price results in the loss of all customers to its competitors, price differentiation is prevented in perfect competition (Varian 1989). In contrast, a monopolistic market gives companies the possibility to exercise a strong market power which allows companies to increase prices without losing their customers (Varian 1989). While researchers now recognize that also duopolists and oligopolists may price differentiate, they still agree that price differentiation requires some level of market power (Philips 1989). As a result, hypothesis 3 proposes that the extent of price differentiation is higher for a lower level of competition.

H3. The lower the level of competition is, the higher the extent of channel-based price differentiation.

3.2. Retailer characteristics

Offline reach. Another important requirement for a company to be able to price differentiate is the ability to separate markets so that consumers are not able to escape the higher price by purchasing the product in the market where the price is low (Philips 1989). Among various criteria, such as demographics, markets can be also separated by distance. In this case, buyers who are far away from the low-price market have to pay a high-price of the market that they are close to because the transactional costs related to purchasing from low-price market are

too high. As such, the transaction costs that consumers have to bear to purchase from a different market will have an influence of the company ability to price differentiate (Miravete 2006). Companies can use various strategies in order to influence these transaction costs. Multi-channel retailers that have only few offline branches may be argued to be able to separate online and offline market well and therefore are more likely to engage in channel-based price differentiation. On the other hand, consumers of a multi-channel retailer that runs many offline branches may easily switch channels and thus jeopardize the channel-based price differentiation. As such fewer offline branches will lead to a higher extent of price differentiation.

H4. The more offline branches a multi-channel retailer operates, the lower the extent of channel-based price differentiation.

Online reach. Similarly to offline reach also online reach is likely to influence the extent of channel-based price differentiation. While the online channel was only used by few consumers at its beginnings, it has experienced a huge increase over the years (online total sales in US equal to \$28,299 mln in 1999 and \$108,324 mln in 2006). This dynamic development and changing situation is likely to affect pricing decisions of multi-channel retailers. Zettelmeyer (2000) recognizes the possibility that multi-channel pricing strategies are likely to depend on the number of potential consumers that would visit the company online channel to conduct the purchase and proposes according pricing strategies. The author develops a theoretical model and shows that if the online reach is low, prices in online and offline channel are likely to differ. With the increasing online reach, competitive factors will lead multi-channel retailers to charge the same prices in online and offline channel (Zettelmeyer 2000). Because multi-channel retailers experience varying online reach levels in terms of number of potential consumers visiting their website, hypothesis 5 proposes that companies with a higher online reach will be less likely to engage in channel-based price differentiation.

H5. The higher the company online reach is, the lower the extent of channel-based price differentiation.

Number of distribution channels. There are many situations when companies forgo the opportunity to price differentiate even though the standard requirements for price differentiation such as heterogeneous consumer tastes or market power are satisfied. One explanation for this state of affairs is high cost of engaging and managing price

differentiation strategies (Anderson and Simester 2001). In the context of multi-channel retailers, excessive cost can be generated with the number of distribution channels. If a retailer operates only two distribution channels, the coordination of channel-based price differentiation imposes less cost than in case of more distribution channels. Therefore, hypothesis 6 proposes that probability of engaging in channel-based price differentiation decreases with the number of channels the retailer operates.

H6. The more distribution channels the retailer operates, the lower the extent of channel-based price differentiation.

Size of the company. Based on their analytical model, Anderson and Dana (2005) argue that a firm that faces lower cost is more likely to engage in price differentiation. Among various factors that can drive the cost structure, size of the company has been argued to play an important role. Big companies can often experience different cost structures and additional cost cuts which are not possible for small companies (Shepard 1991). Due to their superior technology, efficient organization or cheaper purchases, they can enjoy economies of scale and experience decreased average total costs with increasing scale (Mansfield 1983; Tellis 1986). As a result, big companies have more possibilities with regard to pricing products than small companies and are more likely to engage in channel-based price differentiation. Therefore, one can expect a higher extent of price differentiation in case of bigger retailers.

H7. The bigger the retailer is, the higher the extent of channel-based price differentiation.

3.3. Product characteristics

Product type. In addition to market and company characteristics, the nature of the product, its appropriateness for resale and suitability for a given distribution channel are also likely to have an influence on the occurrence of channel-based price differentiation. If the product is appropriate for resale, then consumers facing a lower price may resell the product to consumers facing a higher price which would allow the latter to avoid a higher price and would jeopardize profits from price differentiation. Economic and marketing theories distinguish between goods and services with a common agreement that services are less appropriate for resale. As a result, one can expect higher extent of price differentiation for services than for goods (Philips 1989; Varian 1989; Zettelmeyer 2000).

Other product characteristics are also likely to play a role in the context of channel-based price differentiation. Since online and offline channels differ substantially in their potential to provide information about various product attributes, the suitability of a given channel to sell

a specific product depends on its ability to convey information about this product's attributes (Alba et al. 1997). Therefore, consumers have been shown to differ in their channel preferences depending on the product type (Kacen et al. 2003; Levin et al. 2003). While products such as electronics, books, or travel arrangements have been shown to be purchased both in online and offline channel, clothing is more appropriate for offline channel because it requires physical examination (Kacen et al. 2003; Levin et al. 2003). When both channels are equally appropriate to sell a given product and therefore are similarly valued by consumers, channel-based price differentiation is less likely to occur. In contrast, when one channel significantly outperforms another and the channel valuations differ a lot a possibility for price differentiation for these products arises. Therefore, hypotheses 8 and 9 propose differences in price differentiation extent for different product categories.

H8. The extent of channel-based price differentiation will be higher for services than for goods.

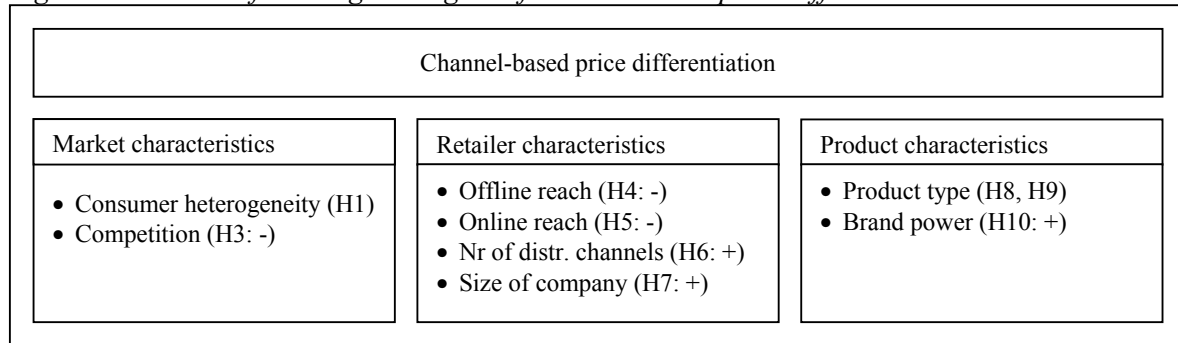
H9. The extent of channel-based price differentiation will depend on the product category.

Brand power. When a company does not possess market power, it can never be successful in charging differential prices (Philips 1989; Varian 1989) which is reflected in hypothesis 3. Market power, however, does not necessarily require monopolistic markets and may occur also in oligopoly or monopolistic competition. In this case, market power can be achieved by advertisement or public relations activities that help to build a strong brand. Strong brands have been claimed to exhibit more power in the market and as a result they offer companies more options for pricing strategies (Leuthesser 1988). Additionally, strong brands decrease consumers' price sensitivity (e.g., Kalra and Goodstein 1998) which gives additional possibilities with regard to charging differential prices. In a similar vein, an empirical study that was conducted in the gasoline market shows that retailers with stronger brands are more likely to price differentiate (Iyer and Seetharaman 2003). Therefore, we propose a higher extent of price differentiation for more powerful brands.

H10. The higher the brand power is, the higher the extent of channel-based price differentiation.

Figure 1 presents the overview of the hypotheses.

Figure 1. Factors influencing the degree of channel-based price differentiation.



4. Empirical studies

In order to address research questions posed in this paper, two empirical studies are conducted. The aim of study 1 is to analyze whether and to what extent multi-channel retailers engage in channel-based price differentiation. The aim of study 2, that was conducted 8 months after study 1, is to check the robustness and persistence of results of study 1 and additionally analyze the factors that influence the extent of channel-based price differentiation.

4.1. Study 1

4.1.1. Data

The data contains price observations for 57 multi-channel retailers from Germany. For each retailer prices in online and offline channel for 20 randomly chosen products resulting in 1,140 observations were collected between June and July 2005. Prices in online and offline distribution channels were checked on the same day. The sample includes multi-channel retailers from various industries.

4.1.2. Results

The comparison of prices charged in online and offline distribution channel provides the evidence for channel-based price differentiation. The average difference between offline and online prices for the same product across all products is equal to 3.75 Euros (3% of the offline price) and is significantly different from 0 ($p < 0.01$, $n = 1,140$). These results are in contrast to Ancarani and Shankar (2004) who show that on average the differences between prices in online and offline channel are not significant. As such, hypothesis H1 is supported.

However, the results show that prices offline are on average higher than prices online which contradicts hypothesis H2.

The analysis on the retailer level shows that 67% of the analyzed multi-channel retailers charged the same prices in both channels while 33% engaged in channel-based price differentiation. Among retailers that engaged in price differentiation, 58% charged higher prices in offline channel, 16% charged higher prices in online channel, and remaining 26% followed a mixed strategy. These results again provide no support for hypothesis H2. For retailers that engaged in channel-based price differentiation price differences were observed for 74% of the analyzed assortment.

On the product level, the analysis shows that among 1,140 products, 25% have differential prices in online and offline channel. For these products the average price gap is equal 15.21 Euros and constitutes 13% of the offline price. For 75% of these products, the price offline is higher while for the remaining 25% the price offline is lower. To sum up, the results of study 1 show that multi-channel retailers engage in channel-based price differentiation which contradicts previous research in this area.

4.2. Study 2

4.2.1. Data

Similarly to study 1, the data includes price observations for online and offline channel for 1,705 randomly chosen products sold by 63 multi-channel retailers in Germany. The data was collected between March and May 2006 for various industries. Prices in online and offline channel were collected on the same day.

In addition to prices in online and offline channel, further information about retailers and market was gathered to analyze the factors that influence the decision to engage in channel-based price differentiation. Below, the operationalization of factors proposed in hypotheses H3-H9 is provided together with information of their sources. Level of competition is measured as the number of websites that are similar to a website of a given multi-channel retailer reported by google.com. In order to build strong brands, companies invest in advertising and public relation activities to increase its presence in the market. Therefore, brand power is operationalized as a number of hits for a given brand name reported by search engine google.com. It is assumed that higher number of hits represents higher brand power. Further, alexa.com is used to obtain the information about the online reach of each multi-channel retailer which is defined as a percentage of global Internet users who visit this

website. Then, based on the retailers' websites, the information about the number of offline branches, the turnover, and number of distribution channels for each multi-channel retailer is collected. Offline branches are used to operationalize offline reach whereas turnover serves as a proxy for company size. Lastly, products are classified into 7 categories: services, clothing and accessories, house wares (e.g., furniture), cosmetics, electronics, leisure (e.g., books, DVD), and food. The categories are chosen in such a way to be able to distinguish between products and services, durables (i.e., electronics) and non-durables (i.e., food), search goods (i.e., electronics) and experience goods (i.e., cosmetics), products with a need for a physical examination (i.e., clothing) and products without such a need (leisure).

4.2.2. Methodology

The aim of study 2 is not only to analyze the occurrence but also to examine the factors that influence the extent of channel-based price differentiation. This analysis takes into account two decisions that a multi-channel retailer faces: first, he decides whether to engage in price differentiation or not, and second, in case of exercising price differentiation, he decides upon the price difference between online and offline channel (i.e., price gap). In order to model these two decisions a tobit II model is used that consists of two specifications: first, the probit model describes whether a dependent variable (i.e., price gap) is zero or positive, and second, the truncated regression model is used to analyze positive values of the dependent variable (Amemiya 1984) resulting in:

$$(1) \quad y_{ij} = 0 \quad \text{if } y_{ij}^* = \alpha X_{ij} + \varepsilon_{1ij} \leq 0$$

$$(2) \quad y_{ij} = \beta X_{ij} + \varepsilon_{2ij} \quad \text{if } y_{ij}^* = \alpha X_{ij} + \varepsilon_{1ij} > 0$$

where y_{ij} is the absolute price gap between offline and online channel for retailer i product j which is equal to 0 if the unobserved latent variable y_{ij}^* is smaller than or equal to 0 and positive if the unobserved latent variable y_{ij}^* is larger than 0 and X_{ij} contains explanatory variables including an intercept. Tobit II model is very similar to tobit I model but it is more flexible because it allows for different effects of explanatory variables on the decision whether to price differentiate or not and on the size of the price gap.

4.2.3. Results

The analysis of prices charged in online and offline channel shows that, on average, offline prices are significantly higher than online prices for the same product ($p < 0.00$) with the price gap equal to 2.60 Euros which constitutes 5% of the average offline price. These results again

contradict the findings of Ancarani and Shankar (2004) who claim no significant price differences across channels. These results provide support for hypothesis H1. However, no support for hypothesis H2 that predicted higher price level in online channel than in offline channel is found.

The analysis on the retailer level shows that 40% of the analyzed multi-channel retailers charge consistent prices across channels while 60% engage in channel-based price differentiation and charge differential prices for identical product in online and offline channels. Among retailers that engage in price differentiation, 37% charge always higher prices offline, 8% charge always higher prices online and the remaining 55% exercise a mixed strategy. The companies that engage in price differentiation exercise this strategy on average with regard to 53% of the analyzed assortment and 6% of the companies exercised price differentiation for the whole assortment analyzed.

The analysis on the product level shows that among 1,705 products price differentiation is applied for 34% of all cases (i.e., 572 products). For the products with differential prices the average price gap is equal to 7.75 Euros which constitutes 13% of the offline price. For 63% of analyzed products, the price offline is higher while for the remaining 37% the price offline is lower.

Since study 1 and study 2 were conducted in different time periods (i.e., 2005 for study 1 and 2006 for study 2), one can compare their results in order to analyze the development of channel-based price differentiation over time. Table 1 shows that over time the percentage of multi-channel retailers that engage in channel-based price differentiation increased from 33% to 60% which results in more products for which price differences between channels is observed (increase from 25% to 34%). This change over time provides additional support for hypothesis H1. Further, comparison of the percentage of multi-channel retailers charging higher prices offline shows a significant drop from 58% to 37% which results in a lower number of products with higher prices offline (75% compared to 63%). These results imply that even though hypothesis H2 is rejected, the market tends to move in its direction. With regard to the size of the price gap, Table 1 shows a decrease in the nominal value, whereas the relative price gap remains constant and is equal to 13% in both studies.

Table 1. Comparison of channel-based price differentiation occurrence in time.

| Comparison criteria | Study 1 | Study 2 |
|--|---------|---------|
| Percentage of multi-channel retailers that engage in channel-based price differentiation | 33% | 60% |
| Percentage of products with differential prices | 25% | 34% |
| Percentage of multi-channel retailers charging always higher prices in offline channel | 58% | 37% |
| Percentage of products with higher prices in offline channel | 75% | 63% |
| Average price gap for all products (Euro) | 3.75 | 2.60 |
| Relative price gap for all products (percentage of offline price) | 3% | 5% |
| Average price gap for products with differential prices (Euro) | 15.21 | 7.75 |
| Relative price gap for products with differential prices (percentage of offline price) | 13% | 13% |

In the next step, the factors influencing the decision to engage in channel-based price differentiation are analyzed. Table 2 presents the results of tobit II model together with the results of an alternative tobit I model as well as the results of a separately estimated probit model and a linear regression. The results of the models are fairly similar and almost all the effects are consistent across different model specifications. Only the effect of brand power and product is not entirely consistent across models.

The results show that level of competition has a significant negative influence on the extent of channel-based price differentiation in terms of probability of observing price differentiation as well as the size of the price gap between channels (-0.0335 and -0.9308 respectively, $p < 0.01$). These results support hypothesis H3. With respect to offline and online reach, no significant effect is found for the former and a significant negative effect is found for the latter with regard to the probability of observing price differentiation (-0.0024, $p < 0.01$) and size of the price gap (-0.0668, $p < 0.01$). As such, no support for hypothesis H4 and a strong support for hypothesis H5 is provided. Further, the number of distribution channels that multi-channel retailers operate has a negative influence on the extent of channel-based price differentiation (-0.0938 for the probability of engaging in price differentiation, $p < 0.05$, and -2.4957 for the price gap, $p < 0.05$) which supports hypothesis H6. Next, company turnover used as a proxy for company size has been found to have a significant positive effect on the extent of price differentiation occurrence (0.0009 for the probability of engaging in price differentiation, $p < 0.01$ and 0.0252 for the price gap, $p <$

0.01). This positive effect supports hypothesis H7. While previous effects have been consistent for both probability of engaging in price differentiation strategy and the size of the price gap, the effect of brand power has no significant effect on the former and a significantly positive effect on the latter (0.0079, $p < 0.05$). These results imply that multi-channel retailers make their decision regarding price differentiation independent of the brands they carry but having decided to price differentiate they set higher price gaps for the strongest brands in their assortment. As such, hypothesis H10 is partly supported.

Lastly, the results show that product type indeed influences the extent of price differentiation which supports hypothesis H9. Since almost all product type parameters are significant and negative, the extent of channel-based price differentiation is highest in case of services that were used as a reference product type. Thus, also hypothesis H8 is supported. The comparison of the size of the product type parameters shows the lowest level of price differentiation for clothing, house wares, and leisure (i.e., books, DVD) and the highest level of price differentiation for electronics and food. The results of ANOVA additionally support these findings and shows significant differences in the extent of price differentiation across product types ($p < 0.01$). Nevertheless, these results do not support the expectation that higher price differentiation should be observed in case of products for which channel valuations differ most (e.g., clothing).

Table 2. Factors influencing the willingness to engage in channel-based price differentiation.

| | Probit model (price differentiation) | Linear regression (price gap) | Tobit I | Tobit II | |
|----------------------------|--|----------------------------------|-------------|--------------------------|-------------|
| | | | | Price differentiation | Price gap |
| Constant | 2.5225*** | 13.9182*** | 42.2481*** | 1.4472*** | 42.6109*** |
| Competition | -0.0447*** | -0.1749** | -0.9410*** | -0.0335*** | -0.9308*** |
| Offline reach | -0.0000 | 0.0001 | -0.0004 | -0.0000 | -0.0004 |
| Online reach | -0.0025*** | -0.0212*** | -0.0660*** | -0.0024*** | -0.0668*** |
| Nr of channels | -0.1265*** | 0.1912 | -2.5070*** | -0.0938** | -2.4957** |
| Turnover | 0.0015*** | 0.0146*** | 0.0253*** | 0.0009*** | 0.0252*** |
| Brand power | 0.0004** | 0.0041** | 0.0079** | 0.0003 | 0.0079** |
| Product | | | | | |
| Clothing | -2.1696*** | -7.9186*** | -44.2197*** | -1.5824*** | -44.4301*** |
| House wares | -1.8022*** | -8.2624*** | -35.9778*** | -1.2689*** | -36.4466*** |
| Cosmetics | -1.0489*** | -9.4546*** | -23.3635*** | -0.7876*** | -23.7685*** |
| Electronics | -0.7282*** | 1.9976 | -6.6940** | -0.1776 | -7.3901 |
| Leisure | -1.5148*** | -7.4216*** | -30.1814*** | -1.0565*** | -30.7745*** |
| Food | -1.0259*** | -12.6550*** | -24.1135*** | -0.8066*** | -24.3304*** |
| Price offline ^a | -0.0003 | 0.0097*** | 0.0127*** | 0.0005*** | 0.0133*** |
| Log likl | -804.2384 | -6920.8155 | -3075.793 | | -3069.629 |

*** Significant at $p < 0.01$, ** Significant at $p < 0.05$, * Significant at $p < 0.10$.

The highest correlation coefficient between the explanatory variables equal to 0.213.

The highest VIF equal to 1.146.

^a In order to account for a price level of analyzed product price in offline channel is included as an additional explanatory variable.

5. Summary and conclusions

This study analyzes the occurrence and factors influencing the decision to engage in channel-based price differentiation by multi-channel retailers. The results show that, in contrast to various studies assuming or reporting consistent prices across online and offline channels (Ancarani and Shankar 2004; Pan et al. 2002; Tang and Xing 2001), many multi-channel retailers do engage in channel-based price differentiation. As such they recognize the possibility to increase their profits by charging differential prices.

Nevertheless, current multi-channel pricing practices seem to be suboptimal. First of all, whereas inverse elasticity rule would suggest charging higher prices in online channel, multi-channel retailers charge on average higher prices in offline channel. These practices may be driven by novelty of online channel or a very high competition in online environment driven by pure online players. Nevertheless, the analysis over time shows a changing trend in a sense that the number of retailer charging higher prices offline decreases over time.

Second, while the highest extent of channel-based price differentiation should be expected with regard to products for which channel valuations differ most (e.g., clothing which is more appropriate for offline channel), the empirical analysis does not support this notion. Biggest price gaps are found for such products as for example electronics that are equally appropriate for both online and offline channel (Kacen et al. 2003; Levin et al. 2003). Therefore, even though retailers recognized the possibility for increasing profits by charging differential prices across channels, they still need to improve their strategies.

With regard to factors influencing the decision to engage in channel-based price differentiation the results of this study support the validity and robustness of standard microeconomic theory. The highest occurrence of price differentiation has been observed in case of big companies that have market power, are able to separate markets and incur low cost for managing price differentiation strategy. Although the brand power of carried products has no influence on the decision to engage in price differentiation, once such a decision is taken multi-channel retailers tend to set higher price gaps for these products.

References

- Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces. *Journal of Marketing*, 61(July), 38-53.
- Amemiya, T. (1984). Tobit Models: A Survey. *Journal of Econometrics*, 24(1), 3-61.
- Ancarani, F., & Shankar, V. (2004). Price Levels and Price Dispersion Within and Across Multiple Retailer Types: Further Evidence and Extension. *Journal of the Academy of Marketing Science*, 32(2), 176-187.
- Anderson, E. T., & Dana, J. (2005). When Is Price Discrimination Profitable?. Working Paper, Kellogg School of Management.
- Anderson, E. T., & Dana, J. (2006). Integrating Models of Price Discrimination. Working Paper, Kellogg School of Management.
- Anderson, E. T., & Simester, D. I. (2001). Research Note: Price Discrimination as an Adverse Signal: Why an Offer to Spread Payments May Hurt Demand. *Marketing Science*, 20(3), 315-327.
- Asheraft, D. (2001). The Multichannel Pricing Challenge - Managing Customer Service in Stores and on the Internet - Brief Article. *DSNRetailing Today*, 16(Jan1), URL: http://findarticles.com/p/articles/mi_m0FNP/is_1_40/ai_69674086, retrieved on 03.05.2007.
- Bakos, Y. (1997). Reducing Buyer Search Costs: Implications for Electronic Marketplaces. *Management Science*, 43(12), 1676-1692.
- Besanko, D., Dubé, J.-P., & Gupta, S. (2003). Competitive Price Discrimination Strategies in a Vertical Channel Using Aggregate Retail Data. *Management Science*, 49(9), 1121 - 1138.
- Brynjolfsson, E., & Smith, M. D. (2000). Frictionless Commerce? A Comparison of Internet and Conventional Retailers. *Management Science*, 46(4), 563-585.
- Campbell, M. C. (1999). Perceptions of Price Unfairness: Antecedents and Consequences. *Journal of Marketing Research*, 36(May), 187-199.
- Chiang, K.-P., & Dholakia, R. R. (2003). Factors Driving Consumer Intention to Shop Online: An Empirical Investigation. *Journal of Consumer Psychology*, 13(1&2), 177-183.

- Chintagunta, P. K., Dubé, J.-P., & Singh, V. (2003). Balancing Profitability and Customer Welfare in a Supermarket Chain. *Quantitative Marketing and Economics*, 1(1), 111-147.
- Chu, J., Chintagunta, P. K., & Vilcassim, N. J. (2007). Assessing the Economic Value of Distribution Channels: An Application to the Personal Computer Industry. *Journal of Marketing Research*, 44(1), 29-41.
- Degeratu, A. M., Rangaswamy, A., & Wu, J. (2000). Consumer Choice Behavior in Online and Traditional Supermarkets: The Effects of Brand Name, Price and Other Search Attributes. *International Journal of Research in Marketing*, 17(1), 55-78.
- Del Franco, M., & Chiger, S. (2002). Multiple Views of Multichannel Promos. *Catalog Age*, 19(13), 1-4.
- Deneckere, R. J., & McAfee, R. P. (1996). Damaged Goods. *Journal of Economics and Management Strategy*, 5(2), 149-174.
- Dulleck, U., & Kerschbamer, R. (2005). Price Discrimination via the Choice of Distribution Channels. Working Paper, Johannes Kepler University of Linz.
- Dzienziol, J., Eberhardt, M., Renz, A., & Schackmann, R. (2002). Multi-channel pricing for financial services. System Sciences, 2002. HICSS. Proceedings of the 35th Annual Hawaii International Conference on System Sciences.
- Gerstner, E., & Hees, J. D. (1995). Pull Promotions and Channel Coordination. *Marketing Science*, 14(1), 43-60.
- Gerstner, E., Hees, J. D., & Holthausen, D. M. (1994). Price Discrimination Through a Distribution Channel: Theory and Evidence. *The American Economic Review*, 84(5), 1437-1445.
- Iyer, G. (1998). Coordinating Channels Under Price and Nonprice Competition. *Marketing Science*, 17(4), 338-355.
- Iyer, G., & Seetharaman, P. B. (2003). To Price Discriminate or Not: Product Choice and the Selection Bias Problem. *Quantitative Marketing and Economics*, 1(2), 155-178.
- Jensen, T., Kees, J., Burton, S., & Turnipseed, F. L. (2003). Advertised Reference Prices in an Internet Environment: Effects on Consumer Price Perceptions and Channel Search Intentions. *Journal of Interactive Marketing*, 17(2), 20-33.
- Jeuland, A. P., & Shugan, S. M. (1983). Managing Channel Profits. *Marketing Science*, 2(3), 239-272.
- Kacen, J. J., Hess, J. D., & Chiang, W.-y. K. (2003). Bricks or Clicks? Consumer Attitudes Toward Traditional Stores and Online Stores. Working Paper, University of Houston.

- Kalra, A., & Goodstein, R. C. (1998). The Impact of Advertising Positioning Strategies on Consumer Price Sensitivity. *Journal of Marketing Research*, 35(2), 210-224.
- Khan, R. J., & Jain, D. C. (2005). An Empirical Analysis of Price Discrimination Mechanisms and Retailer Profitability. *Journal of Marketing Research*, 42(4), 516-524.
- Leslie, P. (2004). Price Discrimination in Broadway Theater. *RAND Journal of Economics*, 35(3), 520-541.
- Leuthesser, L. (1988). Defining, Measuring, and Managing Brand Equity. *Marketing Science Report*, 88-104.
- Levin, A. M., Levin, I. P., & Health, C. E. (2003). Product Category Dependent Consumer Preference for Online and Offline Shopping Features and Their Influence on Multichannel Retail Alliances. *Journal of Electronic Commerce Research*, 4(3), 85-93.
- Lynch, J. G., & Ariely, D. (2000). Wine Online: Search Cost Affect Competition on Price, Quality and Distribution. *Marketing Science*, 19(1), 83-103.
- Mansfield, E. (1983). *Principles of Microeconomics*. New York: W. W. Norton & Company.
- McGuire, T. W., & Staelin, R. (1983). An Industry Equilibrium Analysis of Downstream Vertical Integration. *Marketing Science*, 2(2), 161-191.
- Miravete, E. (2006). Price Discrimination Theory. In L. Blume & S. Durlauf (Eds.), *The New Palgrave Dictionary of Economics*. London: Palgrave Macmillan.
- Montgomery, A. L. (1997). Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data. *Marketing Science*, 16(4), 315-337.
- Moorthy, K. S. (1987). Managing Channel Profits: Comment. *Marketing Science*, 6(4), 375-379.
- Mussa, M., & Rosen, S. (1978). Monopoly and Product Quality. *Journal of Economic Theory*, 18(2), 301-317.
- Neslin, S. A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M. L., Thomas, J. S., & Verhoef, P. C. (2006). Challenges and Opportunities in Multichannel Customer Management. *Journal of Service Research*, 9(2), 95-112.
- Pan, X., Ratchford, B. T., & Shankar, V. (2002). Can Price Dispersion in Online Markets Be Explained by Differences in E-Tailer Service Quality? *Journal of Academy of Marketing Science*, 30(4), 433-445.
- Phlips, L. (1989). *The Economics of Price Discrimination* (1 ed.). Cambridge et al.: Cambridge University Press.

- Rao, V. R. (1993). Pricing Models in Marketing. In J. Eliashberg & G. Lilien (Eds.), *Handbook in Operations Research and Marketing Science*. Amsterdam: Elsevier, North Holland.
- Salant, S. W. (1989). When Is Inducing Self-Selection Suboptimal for a Monopolist? *Quarterly Journal of Economics*, 104(2), 391-397.
- Shankar, V., Rangaswamy, A., & Pusateri, M. (2001). The Online Medium and Customer Price Sensitivity. Working Paper, University of Maryland.
- Shepard, A. (1991). Price Discrimination and Retail Configuration. *Journal of Political Economy*, 99(1), 30-53.
- Stokey, N. L. (1979). Intertemporal Price Discrimination. *Quarterly Journal of Economics*, 93(3), 355-371.
- Sullivan, U. Y., & Thomas, J. S. (2004). Customer Migration: An Empirical Investigation Across Multiple Channels. Working Paper, Northwestern University.
- Tang, F.-F., & Xing, X. (2001). Will the Growth of Multi-Channel Retailing Diminish the Pricing Efficiency of the Web? *Journal of Retailing*, 77(3), 319-333.
- Tellis, G. (1986). Beyond the Many Faces of Price: An Integration of Pricing Strategies. *Journal of Marketing*, 50(October), 146-160.
- Varian, H. R. (1989). Price Discrimination. In R. S. a. R. Willing (Ed.), *Handbook of Industrial Organization*. Amsterdam: North-Holland.
- Zettelmeyer, F. (2000). Expanding to the Internet: Pricing and Communication Strategies When Firms Compete on Multiple Channels. *Journal of Marketing Research*, 37(3), 292-308.

Augmented Methods of Conjoint Analysis to Estimate the Willingness to Pay for Multiple-Unit Products

Agnieszka Wolk

Bernd Skiera

Christian Schlereth

Wolk, A., Skiera, B., and Schlereth C. (2007). Augmented Methods of Conjoint Analysis to Estimate the Willingness to Pay for Multiple-Unit Products. Working Paper, University of Frankfurt.

Augmented Methods of Conjoint Analysis to Estimate the Willingness to Pay for Multiple-Unit Products

Abstract

The willingness-to-pay function describes the amount that a consumer is willing to pay for a given quantity of a product, which provides a means to account for a different willingness to pay for each quantity unit. These differences can be captured profitably by using nonlinear pricing schemes, such as flat-rates or two-part tariffs, which are gaining increasing importance in the pricing of services. Existing methods that use survey data to estimate willingness-to-pay functions have received little attention in the literature. Therefore, we develop, validate, and compare augmented methods of conjoint analysis to estimate willingness-to-pay functions. These methods enable the simultaneous prediction of the consumers' service purchase decision, the tariff choice decision, and the usage quantity decision, which allows for analyzing the effect of price changes on market size, market volume, and market value in market simulations. Furthermore, we decompose the effect of price changes in nonlinear pricing structures into market extension, switching, and cannibalization effects.

Keywords: willingness-to-pay function, nonlinear pricing, conjoint analysis, pricing, services.

1. Introduction

The estimation of the consumers' willingness to pay (WTP) remains one of the most important topics in marketing and consistently receives significant attention from academics and practitioners (e.g., Cameron and James 1987; Jedidi and Zhang 2002; Wang et al. 2007; Wertenbroch and Skiera 2002), largely because WTP enables researchers to predict whether a consumer will purchase a given product at a given price and thus estimate demand for a product. Market researchers estimate WTP from either transaction data (revealed preferences) or survey data (stated preferences). Although transaction data have high external validity, prices in the real market vary only within limited ranges (Ben-Akiva et al. 1994). As a result, transaction data might merely imply that the buyer's WTP is at least as high as and the non-buyer's WTP is lower than the posted price. Thus, a consumer's true WTP can remain unknown, preventing marketers from extracting maximum consumer surplus. Moreover, transaction data are unavailable for companies that enter new markets or new products that have not yet been sold in real market conditions (Wertenbroch and Skiera 2002). The use of survey data offers assistance in these frequently occurring situations and thus provides the motivation for our focus on survey data.

Currently, most methods that use survey data to estimate WTP apply to single-unit products that typically include durable goods, such as washing machines, notebook computers, and cars (Jedidi and Zhang 2002; Voelkner 2006). Multiple-unit products, for which the quantities purchased by individual consumers vary according to the prices, have been neglected in contrast. Typical multiple-unit products include telecommunication services like wireless communication or Internet access, TV pay-channels, online music downloads, or car-sharing services. The WTP estimation for multiple-unit products differs from that for single-unit products because the WTP is unique to each quantity unit. These differences allow for the profitable use of nonlinear pricing schedules, which determine the average price based on the consumed quantity. Prominent examples include two-part tariffs (i.e., a usage-independent fixed fee is paid to gain access to the service, and a marginal price is charged for each unit consumed) or flat rates (i.e., a monthly fixed fee with unlimited usage). However, modeling consumer behavior with nonlinear pricing is very challenging because of the interdependency between tariff prices and the quantity demanded (Iyengar et al. 2007; Lambrecht et al. 2007; Train et al. 1987).

We propose an estimation of individual willingness-to-pay functions (WTPF) to adequately capture the special characteristics of multiple-unit products. The WTPF describes the

maximum price that a consumer is willing to pay for a given quantity of a product (Wilson 1993) and thus captures a different willingness to pay for each quantity unit. In addition, it helps account for the interdependency of tariff and usage, because it predicts different usages for different tariffs. As a result, the WTPF is instrumental for analyzing and implementing nonlinear pricing schemes for multiple-unit products, such as services.

Despite their relevance, WTPF have not received much attention in marketing literature. Although they have been used in analytical models (e.g., Oren et al. 1982; Wilson 1993) and estimated in empirical studies using transaction data (e.g., Lambrecht et al. 2007), they have not been estimated using survey-based market research techniques, such as conjoint analysis. The only exception is Iyengar et al. (2007), who use choice-based conjoint analysis to estimate the demand for a multiple-unit product (cellular phone services).

In consideration of this scarce literature, this article develops, validates, and compares methods that use survey data to estimate willingness-to-pay functions for multiple-unit products. Therefore, we develop augmented methods of conjoint analysis that enable the individual prediction of (1) the service purchase decision, (2) the tariff choice decision, and (3) the usage quantity decision. Although conjoint analysis has been often used to estimate the equalization price (i.e., price that induces indifference between two product alternatives; Swait et al. 1993), our focus is on the willingness to pay for the whole product (e.g., Ding 2007; Voelckner 2006). Duality in consumer theory allows for two kinds of specifications of a WTPF: a direct one that expresses WTP as a function of quantity, and an indirect one that expresses WTP as a function of the price. These specifications relate to different elicitation formats that have not previously been compared. Thus, we also compare two elicitation formats empirically. Moreover, we outline how the estimated WTPF predicts the effects of different nonlinear pricing schemes on the number of customers in the market (market size effect), the number of consumed units (market volume effect), and total revenue of the market (market value effect). Finally, we show that the effect of price changes can be decomposed into a market expansion effect (new or lost customers in the market), a switching effect (new or lost customers swapped from or to competitors), and a cannibalization effect (change in behavior of current customers).

This study differs from Jedidi and Zhang's (2002) because our focus is on multiple-unit products instead of single-unit products. It also differs from Iyengar et al. (2007), who focus on three-part tariffs and a method to capture demand uncertainty. Capturing this uncertainty is important in case of three-part tariffs because higher levels of uncertainty favor tariffs with

higher fixed fees and usage allowances (Lambrecht et al. 2007). In contrast, our focus on two-part tariffs does not need to capture uncertainty because it has no influence on the average bill amount. Furthermore, we consider saturation levels for the demand of individual consumers, unlike Iyengar et al. (2007), who run into the danger of predicting a diminishing WTP for units that exceed the inflection point of the quadratic willingness-to-pay function. These negative values do not match economic theory (Kridel et al. 1993; Wilson 1993). In addition, we compare the validity of different elicitation formats and forms of conjoint analysis, such as ranking and choice-based conjoint, and compare our findings with those of contingent valuation methods. Finally, we specifically decompose the revenue changes that result from a price variation.

The remainder of this article is organized as follows: First, we present the theoretical background for estimating WTPF. Second, we develop and describe two specifications that use an augmented form of conjoint analysis to estimate WTPF. Third, we present two empirical studies. The first builds on the duality of consumer theory and compares the validity of two different elicitation formats for estimating WTPF in a ranking-based conjoint setting. The second study builds on those results and compares the validity of different methods of conjoint analysis (ranking and choice-based) and contingent valuation for estimating WTPF. Fourth and finally, we provide concluding remarks.

2. Theoretical background

2.1. Willingness-to-pay function

The willingness-to-pay function describes the maximum price that a consumer is willing to pay for a given quantity of a product (Wilson 1993). In line with previous literature (Kridel et al. 1993; Lambrecht et al. 2007), we assume that WTP increases with the quantity being consumed (Equation (1)), but the corresponding marginal WTP decreases (Equation (2)). We assume there are no (or negligible) income effects, no network externalities, no tariff-specific preferences, no demand uncertainty of consumers, and no differentiation of prices across time zones, regions, or service qualities.

$$(1) \quad \frac{d WTP_i(q_i)}{d q_i} \geq 0 \quad (i \in I, q_i \geq 0),$$

$$(2) \quad \frac{d^2 WTP_i(q_i)}{d q_i^2} \leq 0 \quad (i \in I, q_i \geq 0),$$

where:

- I: index set of consumers,
- q_i : quantity being consumed by the i^{th} consumer, and
- WTP $_i$: willingness to pay of the i^{th} consumer.

For the willingness-to-pay function, we choose a commonly used quadratic functional form that has the desired characteristics of Equations (1) and (2) (e.g., Brown and Sibley 1986; Lambrecht et al. 2007). Additionally, we bound it by a maximum WTP level and include a saturation level of usage. Consequently, the willingness-to-pay function WTP $_{i,j}(q_{i,j})$ of the i^{th} consumer for a quantity $q_{i,j}$ (which depends on the price of the j^{th} tariff) can be expressed as:

$$(3) \quad WTP_{i,j}(q_{i,j}) = \begin{cases} a_i \cdot q_{i,j} - \frac{b_i}{2} \cdot q_{i,j}^2 + c_i & \text{if } q_{i,j} \leq \frac{a_i}{b_i} \\ \frac{a_i^2}{2 \cdot b_i} + c_i & \text{if } q_{i,j} > \frac{a_i}{b_i} \end{cases} \quad (i \in I, j \in J, q_{i,j} \geq 0),$$

where a_i , b_i , and c_i are individual-specific parameters. The two parts of the WTPF guarantee that Equation (1) is satisfied. The marginal willingness-to-pay function (MWTP $_{i,j}(q_{i,j})$) is defined as the derivative of the WTPF and shows the amount that the i^{th} consumer is willing to pay for the q^{th} unit increment of the quantity being consumed:

$$(4) \quad MWTP_{i,j}(q_{i,j}) = \begin{cases} a_i - b_i \cdot q_{i,j} & \text{if } q_{i,j} \leq \frac{a_i}{b_i} \\ 0 & \text{if } q_{i,j} > \frac{a_i}{b_i} \end{cases} \quad (i \in I, j \in J, q_{i,j} \geq 0).$$

The demand function ($q_{i,j}(p_j)$) is the inverse of the i^{th} consumer's marginal willingness-to-pay function if the marginal willingness to pay is substituted by the price p_j of the j^{th} tariff:

$$(5) \quad q_{i,j}(p_j) = \begin{cases} \frac{a_i}{b_i} - \frac{1}{b_i} \cdot p_j & \text{if } p_j \leq a_i \\ 0 & \text{if } p_j > a_i \end{cases} \quad (i \in I, j \in J, p_j \geq 0).$$

Using the concept of duality in consumer theory, we substitute Equation (5) into Equation (3) and thus achieve an indirect specification of WTP as a function of prices. In the case of a two-part tariff j^{th} with a marginal price p_j , we have:

$$(6) \quad WTP_{i,j}(p_j) = \begin{cases} \frac{a_i^2 - p_j^2}{2 \cdot b_i} + c_i & \text{if } p_j \leq a_i \\ 0 & \text{if } p_j > a_i \end{cases} \quad (i \in I, j \in J, p_j \geq 0).$$

Unlike demand functions, WTPF can address a willingness to pay for a quantity of zero. For example, as is common in Europe, consumers can receive calls if they have mobile cellular service but do not have to pay for the incoming calls, which creates a usage-independent WTP.

2.2. Calculation of consumer surplus

The consumer surplus of the i^{th} consumer under the j^{th} tariff ($CS_{i,j}(q_{i,j})$) is defined as the difference between the willingness to pay ($WTP_{i,j}(q_{i,j})$) and the bill amount $R_{i,j}(q_{i,j})$ charged for using $q_{i,j}$ units:

$$(7) \quad CS_{i,j}(q_{i,j}) = WTP_{i,j}(q_{i,j}) - R_{i,j}(q_{i,j}) \quad (i \in I, j \in J).$$

In the case of a quadratic WTPF (Equation (3)), the direct consumer surplus specification, expressed as a function of the quantity and the bill amount, is:

$$(8) \quad CS_{i,j}(q_{i,j}) = \begin{cases} a_i \cdot q_{i,j} - \frac{b_i}{2} \cdot q_{i,j}^2 + c_i - R_{i,j} & \text{if } q_{i,j} \leq \frac{a_i}{b_i} \\ \frac{a_i^2}{2 \cdot b_i} + c_i - R_{i,j} & \text{if } q_{i,j} > \frac{a_i}{b_i} \end{cases} \quad (i \in I, j \in J, q_{i,j} \geq 0).$$

We limit our analysis to the consideration of two-part tariffs, for which the bill amount consists of the fixed fee, F_j and the marginal price, p_j , multiplied by the quantity consumed, $q_{i,j}$:

$$(9) \quad R_{i,j}(q_{i,j}) = p_j \cdot q_{i,j} + F_j \quad (i \in I, j \in J, q_{i,j}, p_j, F_j \geq 0).$$

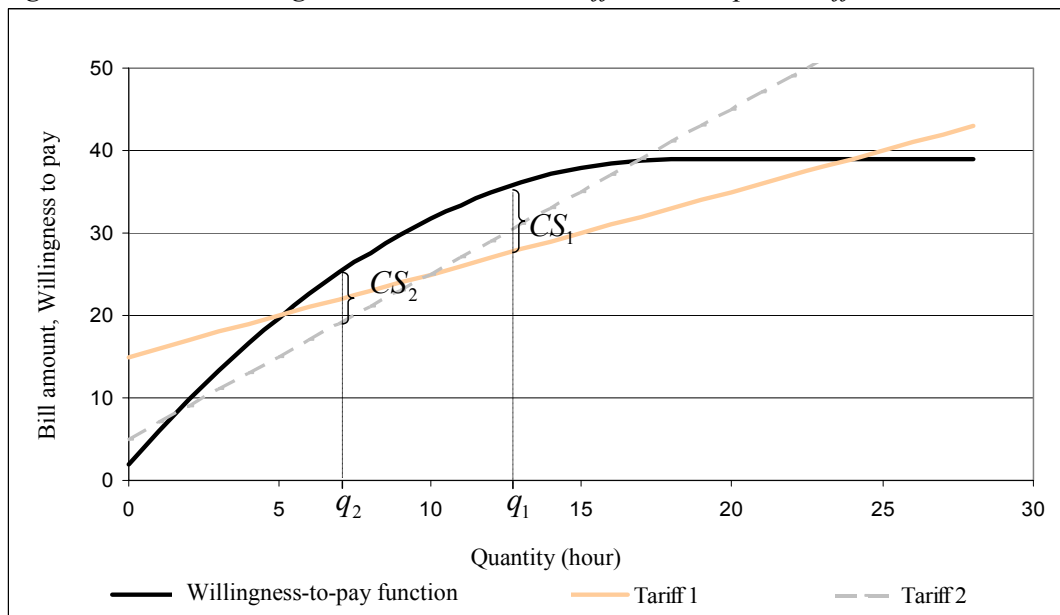
Because Equation (5) enables us to express quantity as a function of price, the consumer surplus in Equation (8) can also be expressed as:

$$(10) \quad CS_{i,j}(p_j, F_j) = \begin{cases} \frac{(a_i - p_j)^2}{2 \cdot b_i} + c_i - F_j & \text{if } p_j \leq a_i \\ c_i - F_j & \text{if } p_j > a_i \end{cases} \quad (i \in I, j \in J, p_j, F_j \geq 0).$$

Thus, consumer surplus can be expressed either directly as a function of the quantity and the bill amount (Equation (8)) or indirectly as a function of prices (Equation (10)). With these equations, Figure 1 illustrates how the WTPF helps predict consumer behavior. Assume that a service provider offers two tariffs to a consumer described by a willingness-to-pay function of $WTP(q_j) = 4.11 \cdot q_j - \frac{0.23}{2} \cdot q_j^2 + 2$, specifically, one tariff with $F_1 = 15$ and $p_1 = 1$ and

another with $F_2 = 5$ and $p_2 = 2$. The corresponding demand function $q_j = 17.87 - 4.35 \cdot p_j$ yields quantities of $q_1 = 13.52$ and $q_2 = 9.17$. The direct (Equation (8)) and indirect (Equation (10)) specifications of consumer surplus lead to $CS_1 = 8.03$ and $CS_2 = 6.68$, respectively. Because the positive consumer surplus of tariff 1 is higher than that of tariff 2, the consumer conducts a purchase and chooses tariff 1. Note that the quantity the consumer will use cannot be determined prior to the tariff choice, and the consumer-specific surplus cannot be revealed unless that consumer has chosen a tariff.

Figure 1. Consumer usage behavior under two different two-part tariffs.



3. Model

Conjoint analysis estimates an interval-scaled individual utility function (e.g., Green and Srinivasan 1990), but WTP and consumer surplus are (monetary) ratio-scaled measures. Therefore, the basic idea of our approach is to augment the various forms of conjoint analysis to transform an interval-scaled utility into a ratio-scaled consumer surplus that can be used to estimate Equations (8) and (10). We next present a four-step procedure that describes our approach for two elicitation formats: (1) "usage format," such that consumer surplus is expressed directly as a function of the quantity and bill amount (Equation (8)), and (2) "tariff format," which expresses consumer surplus indirectly as a function of the tariff prices (Equation (10)).

In the first step, we use conjoint analysis to derive the interval-scaled utility function. For the direct specification (usage format), we express the utility as a function of quantity, the bill

amount, and other variables (e.g., quality of service) (Equation (11)), whereas for the indirect specification (tariff format), the utility is expressed as a function of prices and other variables (Equation (12)). We use a vector model for the bill amount and the fixed fee, and a part-worth model for the quantity and the marginal price. For better illustration, we neglect other attributes here, though their inclusion is straightforward.

$$(11) \quad U_{i,j}^{direct} = pw_i(q_j) - \overline{\omega}_i^{direct} \cdot R_j \quad (i \in I, j \in J),$$

where:

- J: index set of conjoint analysis stimuli (i.e., combinations of quantity and bill amount),
- $U_{i,j}^{direct}$: utility of the j^{th} stimuli in the direct specification of the utility function (i.e., quantity and payment combination) of the i^{th} consumer,
- $pw_i(q_j)$: part-worth utility of the quantity in the j^{th} stimuli for the i^{th} consumer, and
- $\overline{\omega}_i^{direct}$: parameter for the bill amount in the utility function of the i^{th} consumer.

$$(12) \quad U_{i,j}^{indirect} = pw_i(p_j) - \overline{\omega}_i^{indirect} \cdot F_j \quad (i \in I, j \in J),$$

where:

- J: index set of conjoint analysis stimuli (i.e., combination of a fixed fee and a marginal price),
- $U_{i,j}^{indirect}$: utility of the j^{th} stimuli in the indirect specification of the utility function of the i^{th} consumer,
- $pw_i(p_j)$: part-worth utility of the marginal price of the j^{th} stimuli for the i^{th} consumer, and
- $\overline{\omega}_i^{indirect}$: parameter for the fixed fee in the utility function of the i^{th} consumer.

Existing methods for ranking or rating-based, as well as choice-based, conjoint analysis allow us to estimate these utility functions.

The next two steps augment traditional conjoint analysis. In step 2, we divide the interval-scaled values of the utility functions (Equations (11) and (12)) by their corresponding parameter $\overline{\omega}_i$. This step results in utility functions, in which the distances between two utility values are measured in monetary values (Srinivasan 1982). Step 3 is based on the idea that an interval-scaled utility measured in monetary values can be transformed into a ratio-scaled consumer surplus by introducing a zero-point v_i , such that the consumer surplus is 0 for a stimulus that the consumers would not be willing to buy. Information about the utility of the non-purchase option indicates this value in the case of a choice-based conjoint analysis (Ding 2007). However, this step requires additional information for ranking- or rating-based

conjoint analysis, which might be gained by asking the consumer for either the price for a particular quantity or the fixed fee for a tariff with a particular marginal price that would make him or her stop buying the service (Kohli and Mahajan 1991). This information enables us to determine the parameter v_i .

As a result, we transform the interval-scaled utility functions (Equations (11) and (12)) into the following ratio-scaled consumer surplus functions:

$$(13) \quad CS_{i,j}^{conjoint,direct} = v_i^{direct} + \frac{1}{\varpi_i^{direct}} \cdot U_{i,j}^{direct} \quad (i \in I, j \in J),$$

$$(14) \quad CS_{i,j}^{conjoint,indirect} = v_i^{indirect} + \frac{1}{\varpi_i^{indirect}} \cdot U_{i,j}^{indirect} \quad (i \in I, j \in J).$$

Step 4 estimates the parameters of the WTPF on the basis of the idea that the consumer surplus $CS^{conjoint}$ determined using conjoint analysis (Equations (13) and (14)) and the consumer surplus CS^{WTP} determined using the willingness-to-pay function (Equations (8) and (10)) should be as close as possible. Minimizing the sum of squared differences between these two values gives the optimal values of the parameters a_i , b_i , and c_i of the WTPF of the i^{th} consumer. In the case of a quadratic WTPF, Equation (15) emerges for the direct specification and Equation (16) for the indirect specification:

$$(15) \quad \sum_{j \in J} e_{i,j}^2 = \begin{cases} \sum_{j \in J} \left(CS_{i,j}^{conjoint,direct} - \left(a_i \cdot q_{i,j} - \frac{b_i}{2} \cdot q_{i,j}^2 + c_i - R_j \right) \right)^2 & \text{if } q_{i,j} \leq \frac{a_i}{b_i} \\ \sum_{j \in J} \left(CS_{i,j}^{conjoint,direct} - \left(\frac{a_i^2}{2 \cdot b_i} + c_i - R_{i,j} \right) \right)^2 & \text{if } q_{i,j} > \frac{a_i}{b_i} \end{cases} \rightarrow Min!$$

$(i \in I, a_i, b_i, c_i, q_{i,j} \geq 0).$

$$(16) \quad \sum_{j \in J} e_{i,j}^2 = \begin{cases} \sum_{j \in J} \left(CS_{i,j}^{conjoint,indirect} - \left(\frac{(a_i - p_j)^2}{2 \cdot b_i} + c_i - F_j \right) \right)^2 & \text{if } p_j \leq a_i \\ \sum_{j \in J} \left(CS_{i,j}^{conjoint,indirect} - (c_i - F_j) \right)^2 & \text{if } p_j > a_i \end{cases} \rightarrow Min!$$

$(i \in I, a_i, b_i, c_i, F_j, p_j \geq 0).$

In the absence of measurement errors, both models should provide the same parameter estimates. However, different elicitation formats might lead to different results, because some consumers may have more knowledge about the quantity they consume than the price they

pay (or vice versa). Thus, a comparison of the validity of both elicitation formats helps determine which elicitation format to use.

5. Empirical study 1

We conduct two empirical studies to validate and compare our augmented models of conjoint analysis. In the first study, we compare the validity of two different elicitation formats for estimating WTPF in a ranking-based conjoint setting. We also analyze the influence of different attribute levels in the conjoint task and the use of a specific functional form for the WTPF on the stability of the results.

The second study builds on those results and compares the validity of different methods of conjoint analysis (ranking and choice-based) and contingent valuation for estimating WTPF. We also compare the results of our approach with those from a traditional conjoint analysis.

5.1. Study design

In our empirical study, we use survey data to estimate the WTPF for access to the Internet, which is particularly useful for companies that wish to enter the market or have not previously adjusted their prices. Respondents rank their preferences from 1 to 16 for all tariff combinations that feature monthly fixed fees and marginal prices (tariff format), as well as for combinations of usage quantities and bill amounts (usage format). Note that we do not ask consumers to make any statements regarding their expected usage behavior; instead, we use their stated rankings for the estimation of the parameters of the WTPF (see Equation (15) or (16)). Those parameters reveal their intended usage. We monitor the order effects by varying the order of formats.

To analyze the stability of the proposed method, we use two value sets for the attribute levels. For the usage format, the quantity varies between 20 and 140 hours (10 and 90 hours) and the bill amount between 9 and 36 Euros (5 and 32 Euros) for the first value set (second value set). In the case of the tariff format, the fixed fee varies between 5 and 24 Euros (6 and 28 Euros) and the marginal price between 0.30 and 1.20 Euros (0.40 and 1.00) for the first value set (second value set). Our choice of attribute levels is driven by Internet usage levels and market prices at the time of the survey. We randomly assign subjects to the first or second value set. In a separate task, we follow Kohli and Mahajan (1991) and ask for the bill amount for a particular quantity (usage format) and the fixed fee for a tariff with a particular marginal price (tariff format) that would make the respondent stop buying the service. This information indicates the zero-point of the consumer surplus function (parameter v_i).

In addition to the conjoint task, we provide respondents with three holdout tasks. Specifically, we present them with a hypothetical purchase of Internet access where two tariffs and a non-purchase option are available. Respondents indicated whether they would buy the service and which tariff they would choose if they would purchase. In addition, they stated their usage quantity, given the tariff they chose. To check the validity, we gather additional information about respondents' interest in Internet usage, Internet usage levels (average and maximum), and the perceived difficulty of the task (Bettman et al. 1986).

The survey, conducted in 2005, uses undergraduate and graduate students of a major German university, from whom we received 183 completed questionnaires that we use for further analysis: 95 for the first value set (i.e., value set 1) and 88 for the second value set of conjoint analysis attributes (i.e., value set 2). The respondents report an average usage of 34.4 hours per month, which is very close to the average Internet usage of 37.2 hours in Germany (ComScore 2006), and a maximum Internet usage of 52.8 hours per month.

5.2. Estimation and validation of the utility function

In line with the recommendation of Darmon and Rouzies (1994), we use a linear regression to calculate the individual utility functions and provide the results in Table 1. All parameters are significant at $p = 0.05$, the average R^2 ranges from 0.980 to 0.984, and the correlation coefficients between observed and predicted ranks are very high (i.e., 0.993 - 0.994). To test the appropriateness of the use of a vector model for the fixed fee and the bill amount, we follow the recommendation of Hagerty and Srinivasan (1991) and compare the expected mean squared error of prediction (EMSEP) of a vector model and a more flexible (part-worth) model. The results indicate that the use of a vector model is appropriate in most cases.

Table 1. Conjoint analysis validation.

| | Tariff format | | Usage format | |
|--|--------------------|--------------------|--------------------|--------------------|
| | Value set 1 | Value set 2 | Value set 1 | Value set 2 |
| Vector model (vector model for a fixed fee in tariff design and bill amount in usage design) and part-worth model for a marginal price in tariff design and quantity in usage design) | | | | |
| Sign. parameters | 100% | 100% | 100% | 100% |
| Correlation | 0.994 | 0.993 | 0.993 | 0.993 |
| R ² | 0.984 | 0.983 | 0.984 | 0.980 |
| EMSEP | 0.027 | 0.027 | 0.028 | 0.036 |
| Part-worth model (part-worth vector model for all variables) | | | | |
| Sign parameters | 56.8% | 61.4% | 84.2% | 73.9% |
| Correlation | 0.997 | 0.998 | 0.998 | 0.997 |
| R ² | 0.990 | 0.991 | 0.989 | 0.984 |
| EMSEP | 0.026 ^a | 0.022 ^a | 0.027 ^b | 0.038 ^b |

EMSEP: Expected mean squared error of prediction; Sign. parameters: Significance of parameters.

^a – No significant difference compared with the corresponding vector model.

^b – Significant difference compared with the corresponding vector model.

Table 2 reports the parameter estimates and importance weights from the conjoint analysis. The results show, on average, higher importance weights for the fixed fee (bill amount) than for the quantity (marginal price), which implies a lower maximum WTP and lower saturation level. Consumers who put a higher emphasis on a fixed fee try to avoid it at the cost of a higher marginal price. Thus, they are less sensitive to changes in the marginal price because their consumption is rather low. Conversely, their high consumption levels prompt heavy users to put more emphasis on the marginal price. Similarly, consumers who place a higher emphasis on a bill amount rather than quantity consumed can be considered price-sensitive light users. This tendency also is reflected in the consumer surplus specification (Equation (13)) and in Equation (14)), in which, all other being equal, higher ϖ_i lowers the consumer surplus and thus WTP.

Table 2. Parameter estimates from conjoint analysis.

| | Tariff format | | Usage format | |
|---|---------------|--------------|--------------|--------------|
| | Value set 1 | Value set 2 | Value set 1 | Value set 2 |
| Parameter estimates | | | | |
| Part worth for marginal price / quantity 1 ^a | 18.51 (0.97) | 19.29 (0.72) | 13.75 (4.29) | 12.06 (3.54) |
| Part worth for marginal price / quantity 2 | 16.42 (1.98) | 17.53 (1.58) | 16.04 (2.89) | 14.78 (2.11) |
| Part worth for marginal price / quantity 3 | 14.12 (3.27) | 15.82 (2.49) | 17.85 (1.79) | 16.40 (1.27) |
| Part worth for marginal price / quantity 4 | 11.81 (4.43) | 13.98 (3.45) | 19.36 (1.03) | 17.93 (0.65) |
| Fixed fee / bill amount coefficient ^b | -0.47 (.18) | -0.47 (0.12) | -0.37 (0.11) | -0.37 (0.10) |
| Importance weights | | | | |
| Marginal price / quantity ^a | 0.43 (0.23) | 0.33 (0.18) | 0.36 (0.21) | 0.37 (0.19) |
| Fixed fee / bill amount ^b | 0.57 (0.23) | 0.67 (0.18) | 0.64 (0.21) | 0.63 (0.19) |

Standard deviations appear in parenthesis.

^a Marginal price in case of tariff format, and quantity in case of usage format.

^b Fixed fee in case of tariff format, and bill amount in case of usage format.

5.3. Method validation

Table 3 presents the results of the mean values of the estimated parameters of the WTPF and the resulting WTP for certain quantities for both usage and tariff formats, as well as for both value sets used in the conjoint analysis. Parameter a, which drives the increase of the WTPF, ranges from 1.73 to 2.74; as expected, it is higher than parameter b, which is responsible for the decrease in the MWTPF and ranges from 0.15 to 0.32. Parameter c describes the usage-independent WTP and varies between 0.49 and 2.08. On the basis of these estimated individual parameters, we can calculate the WTP for various quantities. For example, the average WTP for 20 hours of Internet access varies between 18.30 and 22.58 Euros, depending on the format and value set.

Table 3. Mean values of the quadratic willingness-to-pay functions.

| Parameter | Value set 1 | | | Value set 2 | | | Value set comparison | |
|----------------|---------------------|---------------------|----------------------|---------------------|---------------------|----------------------|--|---|
| | Usage format | Tariff format | Sign. of differences | Usage format | Tariff format | Sign. of differences | Sign. of differences for usage formats | Sign. of differences for tariff formats |
| a _i | 1.99 (1.49-2.50) | 2.74 (2.25-3.22) | 0.040 | 1.73 (1.37-2.09) | 2.59 (2.16-3.01) | 0.000 | 0.406 | 0.644 |
| b _i | 0.15 (0.09-0.20) | 0.32 (0.23-0.41) | 0.004 | 0.15 (0.10-0.19) | 0.18 (0.13-0.23) | 0.287 | 0.994 | 0.010 |
| c _i | 2.08 (1.66-2.50) | 0.61 (0.42-0.82) | 0.000 | 2.40 (1.66-3.15) | 0.49 (0.33-0.64) | 0.000 | 0.443 | 0.309 |
| WTP(0) (€) | 2.08 | 0.62 | 0.000 | 2.40 | 0.49 | 0.000 | 0.443 | 0.309 |
| WTP(20) (€) | 19.88 | 18.72 | 0.399 | 18.30 | 22.58 | 0.001 | 0.421 | 0.002 |
| WTP(40) (€) | 23.46 | 24.76 | 0.408 | 21.44 | 27.58 | 0.000 | 0.315 | 0.111 |
| WTP(60) (€) | 24.51 | 28.56 | 0.031 | 23.48 | 30.42 | 0.000 | 0.619 | 0.438 |
| WTP(80) (€) | 25.27 | 30.97 | 0.009 | 24.83 | 32.26 | 0.001 | 0.840 | 0.658 |
| Max WTP (€) | 29.30 | 34.93 | 0.065 | 33.44 | 41.95 | 0.168 | 0.447 | 0.196 |
| Saturation (h) | 79.75 | 51.99 | 0.071 | 75.97 | 66.11 | 0.578 | 0.323 | 0.855 |

The 95% confidence interval appears in parenthesis.

Table 3 indicates that the average maximum WTP ranges from 29.30 to 41.95 Euros, which provides face validity, because this range generally corresponds to the current price of Internet access. Furthermore, the average saturation level varies between 51.99 and 79.75 hours and is higher than the average Internet usage of 37.2 hours in Germany (ComScore 2006), which meets our expectation because consumers' usage levels usually lie below their saturation levels. Table 4 indicates that the differences between the usage saturation based on the WTPF and reported maximum Internet usage are not significant ($p < 0.10$) in three out of four formats, which supports the validity of our results. In addition, if WTP reflects respondents' true preference, we should be able to connect them to response patterns related to Internet interest (Diamond and Hausmann 1994). Indeed, we find positive and significant correlation coefficients between Internet interest and the maximum WTP in the tariff format.

Stability. To analyze the stability of our results, we compare the results for the two value sets for the attributes in the conjoint analysis. The prices or quantities used in the conjoint analysis result in statistically different parameters or WTPF values in only two of twenty cases, which implies that the method provides stable results (see last two columns of Table 3).

Internal validity. We analyze internal validity in terms of correlation coefficients between the actual and the predicted rank of the stimuli by the parameters of the WTPF. The Spearman correlation coefficient varies between 0.84 and 0.98, and Kendall's Tau varies between 0.87 and 0.93 (see Table 4). Jedidi and Zhang (2002), who use conjoint analysis to estimate WTP for a durable good (notebook computer) report a Spearman coefficient equal to 0.83, and

Kalish and Nelson (1991) obtain a Spearman correlation coefficient in the range of 0.88-0.96. Thus, we conclude that our results have a high internal validity.

Predictive validity. We use the three holdout choice sets to analyze the predictive validity of our approach. First, we compare self-reported purchase decisions with those predicted by the WTPF. Second, we compare the self-reported and predicted tariff choice and usage quantities. The results in Table indicate that our approach has a high hit rate in predicting the purchase of the service, ranging between 79% and 87%, and a slightly lower hit rate with regard to the tariff choice (56-75%). While usage format oscillates close to the proportional chance criterion of 0.79 for service purchase and 0.56 for tariff choice, tariff format clearly outperforms it. Our results thus are comparable to Jedidi and Zhang (2002) who report a purchase incidence hit rate of 91.8% and product choice hit rates of 60.4% and 54.7%. In contrast, Kalish and Nelson (1991) report lower purchase hit rates (46-62%). As we also show in Table 4, we achieve highly significant correlation coefficients between reported and predicted usage quantity for the tariff format but not for the usage format.

Table 4. Face, internal, and predictive validity for quadratic willingness-to-pay functions.

| | Value set 1 | | Value set 2 | |
|--|--------------|---------------|--------------|---------------|
| | Usage format | Tariff format | Usage format | Tariff format |
| Face validity | | | | |
| Correlation between Internet interest and maximum of willingness to pay | -0.002 | 0.280*** | 0.157 | 0.271** |
| Correlation between reported maximum usage and predicted saturation levels | 0.064 | 0.457*** | 0.162 | 0.195 |
| Internal validity | | | | |
| Kendall's Tau | 0.87 | 0.91 | 0.90 | 0.93 |
| Spearman's correlation coefficient | 0.84 | 0.96 | 0.91 | 0.98 |
| Predictive validity | | | | |
| Service purchase (hit rate) | 0.79 | 0.87 | 0.81 | 0.86 |
| Tariff choice (hit rate) | 0.56 | 0.75 | 0.60 | 0.68 |
| Usage (correlation) | 0.30*** | 0.50*** | 0.02 | 0.61*** |

* Significant at p = 0.10, ** Significant at p = 0.05, *** Significant at p = 0.01.

Comparison of elicitation formats. The results indicate that both elicitation formats lead to significantly different results in terms of parameters, WTPF values, and validity. With regard to face validity, Table 4 shows that the tariff format leads to better results, because its predicted saturation level correlates significantly with the reported maximum level, and the predicted maximum WTP significantly correlates with Internet usage interest. Table 4 also

reveals that the tariff format has higher internal and predictive validities. Furthermore, we analyze the feasibility of both formats according to the perceived difficulty of both and find that the tariff format is perceived as much easier than the usage format ($p < 0.00$). On the basis of these results, we conclude that the tariff format is more suitable than the usage format.

Robustness of the results. To determine the robustness of the results, we also estimate a WTPF based on an exponential demand function, which has attracted considerable interest from researchers in the telecommunications field (e.g., Kridel et al. 1993):

$$(17) \quad q_{i,j}(p_j) = a_i \cdot \exp(-b_i \cdot p_j) \quad (i \in I, j \in J, p_j \geq 0),$$

which corresponds to the following willingness-to-pay function:

$$(18) \quad WTP_{i,j}(q_{i,j}) = \begin{cases} \frac{q_i}{b_i} \cdot (1 + \ln(a_i) - \ln(q_{i,j})) + c_i & \text{if } 0 < q_{i,j} \leq a_i \\ \frac{a_i}{b_i} + c_i & \text{if } q_{i,j} > a_i \end{cases} \quad (i \in I, j \in J, q_{i,j} \geq 0).$$

As we show in Table 5, the tariff format has higher face and internal validity in both value sets. The results also indicate a higher predictive validity for tariff choice and usage in value set 1 and for usage alone in value set 2. These results support the notion that the tariff format leads to better results than the usage format.

Table 5. Face, internal, and predictive validities for the willingness-to-pay function based on exponential demand function.

| | Value set 1 | | Value set 2 | |
|--|--------------|---------------|--------------|---------------|
| | Usage format | Tariff format | Usage format | Tariff format |
| Face validity | | | | |
| Correlation between Internet interest and maximum of willingness-to-pay | 0.113 | 0.325*** | 0.122 | 0.348*** |
| Correlation between reported maximum usage and predicted saturation levels | 0.139 | 0.451*** | -0.044 | 0.141 |
| Internal validity | | | | |
| Kendall's Tau | 0.94 | 0.90 | 0.92 | 0.93 |
| Spearman's correlation coefficient | 0.96 | 0.95 | 0.95 | 0.97 |
| Predictive validity | | | | |
| Service purchase (hit rate) | 0.89 | 0.89 | 0.86 | 0.86 |
| Tariff choice (hit rate) | 0.65 | 0.72 | 0.71 | 0.63 |
| Usage (correlation) | 0.50*** | 0.52*** | 0.24** | 0.54*** |

* Significant at $p = 0.10$, ** Significant at $p = 0.05$, *** Significant at $p = 0.01$.

Furthermore, the results of the two considered functional forms are similar, which indicates that the functional form of the WTPF has only a moderate influence on the results. The correlation coefficients between the WTP of both functional forms for different quantities are very high and significant (i.e., between 0.82 and 0.97, $p < 0.01$), and when we compare the results of Table 3 and Table 6, we note that the differences between the WTP for middle-range quantities are relatively small (i.e., 0.28-3.70 Euros for tariff format and 0.33-3.37 Euros for usage format). However, a comparison of the results for the tariff format in Table 4 and Table 5 shows that the quadratic WTPF achieves a higher validity on average.

Table 6. Mean values of the willingness-to-pay functions based on exponential demand functions.

| Parameter | Value set 1 | | | Value set 2 | | | Value set comparison | |
|-------------|--------------|---------------|----------------------|--------------|---------------|----------------------|------------------------|-------------------------|
| | Usage format | Tariff format | Sign. of differences | Usage format | Tariff format | Sign. of differences | Sign. for usage format | Sign. for tariff format |
| WTP(0) (€) | 5.59 | 0.01 | 0.000 | 8.45 | 0.02 | 0.000 | 0.035 | 0.157 |
| WTP(20) (€) | 16.51 | 19.20 | 0.017 | 16.73 | 23.72 | 0.000 | 0.894 | 0.000 |
| WTP(40) (€) | 20.31 | 25.04 | 0.002 | 20.99 | 29.55 | 0.000 | 0.697 | 0.010 |
| WTP(60) (€) | 22.81 | 29.09 | 0.001 | 24.17 | 33.13 | 0.000 | 0.465 | 0.080 |
| WTP(80) (€) | 24.94 | 32.23 | 0.001 | 26.69 | 35.96 | 0.000 | 0.386 | 0.187 |
| Max WTP (€) | 45.54 | 52.98 | 0.107 | 47.10 | 55.20 | 0.172 | 0.750 | 0.764 |

6. Market simulation

Having validated our approach, we use the estimated individual willingness-to-pay functions to analyze the effect of changes in tariff prices on market size, market volume, and market value. In addition, we decompose the revenue changes into market expansion, switching, and cannibalization effects. We assume that consumers subscribe to a service only if they realize a nonnegative consumer surplus, and in the case of optional tariffs, we assume consumers choose the tariff that maximizes their consumer surplus. We define the market size m_{size} as the number of consumers in the market, the market volume m_{volume} as the number of units sold in the market, and the market value m_{value} as the revenue generated in the market:

$$(19) \quad m_{size} = \sum_{i \in I} \sum_{j \in J} z_{i,j} ,$$

$$(20) \quad m_{volume} = \sum_{i \in I} \sum_{j \in J} q_{i,j} \cdot z_{i,j} ,$$

$$(21) \quad m_{value} = \sum_{i \in I} \sum_{j \in J} R_{i,j} \cdot z_{i,j} ,$$

where the binary variable $z_{i,j}$ indicates whether the i^{th} consumer chooses the j^{th} tariff in a competitive tariff setting.

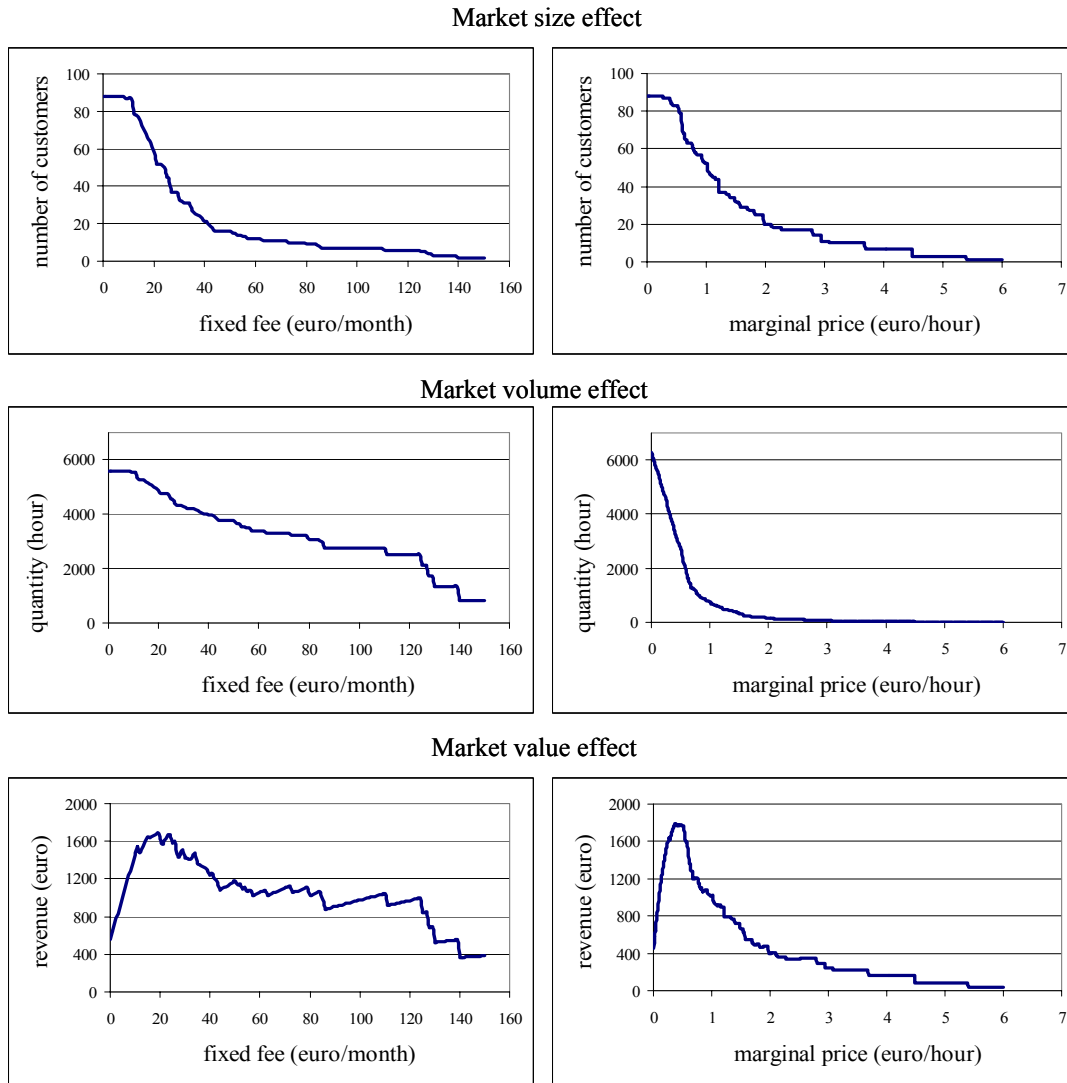
We use the individual quadratic WTPF, estimated for the tariff format in value set 2, to illustrate the effects of changes in tariffs, especially in the fixed fee and the marginal price, on these measures. We analyze the implications of varying the prices (1) in a market with a single tariff with a fixed fee of $F = 5$ and a marginal price of $p = 0.1$ and (2) in a market with two optional tariffs, tariff 1: a flat-rate ($p_1 = 0$ and $F_1 = 16$) and tariff 2: a pay-per-use tariff ($p_2 = 1$ and $F_2 = 0$).

6.1. Single tariff market simulation

Figure 2 shows that, in the presence of a single tariff, the number of customers in the market is more sensitive to changes in the fixed fee than to changes in the marginal price. Conversely, changes in the marginal price influence the market volume more than do changes in the fixed fee. These effects occur because the fixed fee only affects consumer surplus and thus the decision to participate in the market (see Equation (10)), whereas marginal price influences consumer surplus and usage quantity (see Equations (5) and (10)). Therefore, allowing consumers to leave the market is very important for this analysis. If we were to ignore customer attrition, we would likely underestimate the effect of prices (Danaher 2002).

In line with these results, the market value (i.e., revenue generated in the market) reacts much more strongly to changes in the marginal price than to changes in the fixed fee.

Figure 2. Effects of tariff changes in the single tariff market simulation.

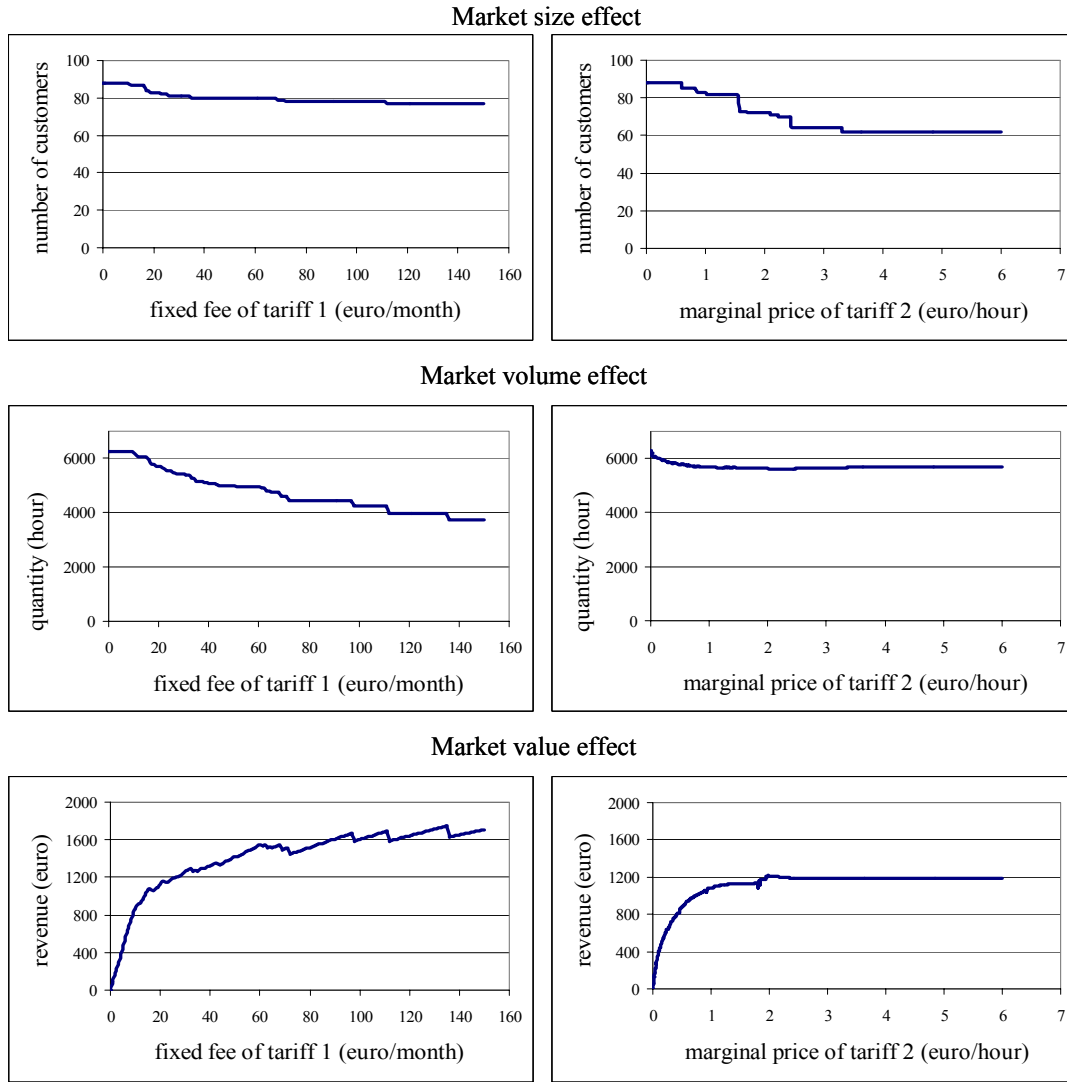


6.2. Optional tariff market simulation

Figure 3 shows that offering optional tariffs leads to weaker effects of changes in the prices of one tariff on market size, volume, and value. The reason is that an increase in price makes consumers leave the market in the single tariff simulation, but when other tariffs are available, consumers switch to the relatively cheaper tariffs instead. Figure 3 also shows that an increase in the fixed fee of tariff 1 causes a stronger decrease in market volume than does an increase in marginal price with tariff 2. A higher fixed fee makes some consumers leave

the market and others switch to the pay-per-use tariff, which also decreases their individual usage in response to the higher marginal price. The effects differ when we increase the marginal price of tariff 2. Whereas the individual usage of consumers who stay with the pay-per-use format decreases, consumers who switch to the flat-rate tariff increase their usage. In our simulations, these effects are approximately equal, so we observe only a small drop in market volume. The effects on market value are stronger for changes in the fixed fee of tariff 1 than for the changes in the marginal price of tariff 2, because an increase in the former skims more consumer surplus from those consumers who continue to use tariff 1. The other consumers do not leave the market but switch to tariff 2. An increase in the marginal price of tariff 2, in contrast, leads to higher revenue from consumers who stay but still makes some consumers leave the market.

Figure 3. Effects of tariff changes in the optional tariff market simulation.



6.3. Decomposition of the effect of tariff changes

Changes in tariff prices lead to changes in the company's revenue and profit (for a clearer explanation, we focus only on revenue, but the extension to profit is straightforward). Revenue changes can have three different sources: a market expansion effect (new or lost customers to the market), a switching effect (new or lost customers from or to competitors), and a cannibalization effect (changes in current customers' behavior). While the first two effects are positive for the company, the third is negative. We denote the set of tariffs of competitors in the market with J^{comp} and the set of own tariffs as J^{own} , then refer to the newly introduced or modified tariff as j' .

The market value m_{value}^0 before the introduction or modification of tariff j' is given by:

$$(22) \quad m_{value}^0 = \sum_{j \in J^{comp}} R_j^0 + \sum_{j \in J^{own} / j'} R_j^0 + R_{j'}^0,$$

where the revenue of the j^{th} tariff is defined as (suppressing the index 0 and 1):

$$(23) \quad R_j = \sum_{i \in I} R_{i,j} \cdot z_{i,j} \quad (j \in J).$$

With a new tariff j' , $R_{j'}^0 = 0$, the market value m_{value}^1 after its introduction is given by:

$$(24) \quad m_{value}^1 = \sum_{j \in J^{comp}} R_j^1 + \sum_{j \in J^{own} / j'} R_j^1 + R_{j'}^1.$$

Subtracting Equation (22) from (24) and rearranging yields:

$$(25) \quad R_{j'}^1 - R_{j'}^0 = (m_{value}^1 - m_{value}^0) + \left(\sum_{j \in J^{comp}} R_j^0 - \sum_{j \in J^{comp}} R_j^1 \right) + \left(\sum_{j \in J^{own} / j'} R_j^0 - \sum_{j \in J^{own} / j'} R_j^1 \right).$$

The term on the left-hand side describes the change in revenue due to the modification of the prices of the j^{th} tariff (or introduction of the new tariff j'). This change in revenue can be decomposed into a market expansion effect $(m_{value}^1 - m_{value}^0)$, a switching effect

$\left(\sum_{j \in J^{comp}} R_j^0 - \sum_{j \in J^{comp}} R_j^1 \right)$, and a cannibalization effect $\left(\sum_{j \in J^{own} / j'} R_j^0 - \sum_{j \in J^{own} / j'} R_j^1 \right)$. A similar procedure

can be used to decompose market size and volume effects.

Table 7 illustrates the decomposition of changes in revenue, number of customers, and usage due to the introduction of an additional tariff 2 by firm A with $F_{A2} = 19$ and $p_{A2} = 0.50$ in our market, where firm A already offers tariff 1 with $F_{A1} = 40$ and $p_{A1} = 0.10$ and firm B offers a tariff with $F_{A2} = 10$ and $p_{A2} = 1.50$. The new tariff generates revenues of 273.61, which can be decomposed into a market expansion effect of 71.51, a switching effect of 113.83, and a cannibalization effect of 88.28. The overall increase in revenue for firm A equals the sum of the market expansion and switching effects ($71.51 + 113.83 = 1296.79 - 1111.46$). A similar procedure decomposes the number of customers and use of the new tariff. That is, the new tariff attracts nine customers: three who are new to the market (market expansion effect), four who switched from firm B (switching effect), and two who previously used firm A's tariff 1 (cannibalization effect). Usage under the new tariff equals 205.23, which is the sum of the market expansion effect (73.24), the switching effect (49.22), and the cannibalization effect

(82.77). Our example thus illustrates that firm A benefits from both switching and market expansion effects but also suffers strongly from cannibalization effects.

Table 7. Decomposition of changes in revenues, number of customers, and usage into market expansion, switching, and cannibalization effects.

| | Situation 0 | | | | Situation 1 | | | | Market expansion effect | Switching effect | Cannibalization effect |
|-------------------------|-------------|--------|----------|----------|-------------|--------|----------|----------|-------------------------|------------------|------------------------|
| | Firm A | Firm B | Total | | Firm A | | Total | | | | |
| | | | | Tariff 1 | Tariff 2 | Total | Firm B | Total | | | |
| Fixed fee (€/month) | 40 | 10 | | 40 | 19 | 10 | | | | | |
| Marginal price (€/hour) | 0.1 | 1.5 | | 0.1 | 0.5 | 1.5 | | | | | |
| Number of customers | 18 | 19 | 37 | 16 | 9 | 15 | 25 | 40 | 4 | 2 | |
| Total usage (h) | 3914.59 | 164.95 | 4079.54 | 3831.82 | 205.23 | 115.74 | 4037.05 | 4152.78 | 73.24 | 49.22 | 82.77 |
| Revenue (€) | 1,111.46 | 437.43 | 1,548.89 | 1,023.18 | 273.61 | 323.60 | 1,296.80 | 1,620.40 | 71.51 | 113.83 | 88.28 |

7. Empirical study 2

The results of Study 1 clearly show that the use of tariffs as stimuli (tariff format) leads to a higher validity than the use of a combination of quantities and bill amounts (usage format). It also indicates how these results can be used easily to evaluate the effect of price changes on market size, market volume, and market value and to decompose those effects into market extension, switching, and cannibalization effects. However, it does not reveal how ranking-based conjoint analysis compares with other forms of conjoint analysis, in particular choice-based conjoint analysis or a contingent valuation approach that asks respondents directly for their WTP for various quantities of a service (Mitchell and Carson 1989). Study 2 aims to overcome these limitations.

7.1. Study design

Similar to Study 1, we estimate WTPF for access to the Internet. Respondents completed (in varying order) the following three tasks: (1) ranking 16 tariffs (i.e., ranking-based conjoint) and stating the fixed fee for a tariff with a particular marginal price that would make them stop buying (similar to the task in Study 1),¹ (2) choosing an alternative among two different tariffs and a non-purchase option for 21 choice tasks² (i.e., choice-based conjoint), and (3) stating their WTP for various quantities (i.e., contingent valuation). Similar to Study 1, all tariffs are combinations of monthly fixed fees and marginal prices, ranging between 11 and 32 Euros for the fixed fee and 0.30 and 1.20 Euros per hour for the marginal price. We provide respondents with 5 holdout tasks, in which they must make purchase, tariff choice, and usage quantity decisions in a hypothetical purchase situation to obtain access to the Internet. In addition, we inquire about task difficulty and Internet usage knowledge on a 5-point Likert scale as well as about Internet usage levels.

The online survey, conducted among undergraduate and graduate students of a major German university in 2007, resulted in 206 completed questionnaires for further analysis. The respondents reported an average usage of 54.49 hours per month and a maximum Internet usage of 90.79 hours per month. On average, the respondents also report high knowledge about current Internet usage (4.18).

¹ We also compare the results from an open question with those we obtain by asking respondents to place a "limit card" on top of the stimulus with the tariff that they would no longer buy. The results are similar.

² Moore (2004) states that a proper comparison of ranking-based and choice-based conjoint analysis requires that the number of choice sets is equal to or higher than the corresponding number of profiles.

7.2. Estimation and validation of the willingness-to-pay functions

We use the same approach as in Study 1 to calculate the WTPF for the ranking-based conjoint task.³ We obtain corresponding functions for the choice-based conjoint task by estimating a hierarchical Bayes multinomial logit choice model. In the case of the contingent valuation, we estimate the parameters a_i , b_i , and c_i by minimizing the squared differences between the values of the WTP for the various quantities reported in the survey and the values resulting from Equation (3). Table 8 presents the results of the mean values of the estimated parameters of the WTPF and the resulting WTP for the three different methods.

Convergent validity. Table 8 reveals relatively small differences for WTP between ranking-based and choice-based conjoint analysis for the middle range quantities (i.e., average absolute difference in WTP for quantities of 0, 20, 40, 60, and 80 hours is 4.01 Euros). In contrast, the differences between conjoint analyses and contingent valuation are high. The average absolute difference in WTP for quantities of 0, 20, 40, 60, and 80 hours between the contingent valuation and ranking-based and choice-based conjoint is equal to 11.08 and 15.07, respectively. These results suggest a reasonably high convergent validity between ranking-based and choice-based conjoint but a rather low convergent validity between conjoint analysis and contingent valuation.

Table 8. Willingness-to-pay function estimates.

| Parameter | Ranking-based conjoint analysis | Choice-based conjoint analysis | Contingent valuation |
|----------------|------------------------------------|-----------------------------------|-------------------------|
| a_i | 2.30 (2.04-2.56) | 2.64 (2.03-3.24) | 1.76 (1.46-2.05) |
| b_i | 0.16 (0.12-0.20) | 0.52 (0.16-0.89) | 0.22 (0.16-0.27) |
| c_i | 0.36 (0.23-0.49) | 0.40 (0.16-0.64) | 1.38 (1.02-1.74) |
| WTP(0) (€) | 0.36 | 0.40 | 1.38 |
| WTP(20) (€) | 22.92 | 26.91 | 13.91 |
| WTP(40) (€) | 31.51 | 37.14 | 18.75 |
| WTP(60) (€) | 36.85 | 42.27 | 21.53 |
| WTP(80) (€) | 40.41 | 45.39 | 23.13 |
| Max WTP (€) | 49.48 | 64.15 | 25.24 |
| Saturation (h) | 84.63 | 95.10 | 81.73 |

The 95% confidence interval appears in parenthesis.

³ We also use a hierarchical Bayes regression model for the utility estimation in the first step and find no significant differences with the values of the WTPF reported here.

Feasibility. We evaluate feasibility by analyzing the difficulty and time needed to accomplish each task. To measure difficulty, we form a factor based on Bettman et al. (1986) work. The Cronbach's alpha (variance extracted) equals to 0.81 (57%) for ranking-based conjoint analysis, 0.83 (60%) for choice-based conjoint, and 0.85 (63%) for contingent valuation. Respondents generally perceived ranking-based conjoint analysis as the most difficult of the tasks (3.01), followed by choice-based conjoint (2.89) and contingent valuation (2.77) (differences significant at $p < 0.10$). In a similar vein, respondents needed an average of 250.94 seconds to accomplish the ranking-based conjoint task, 208.66 seconds for the choice-based conjoint task, and 143.15 seconds for the contingent valuation task. These differences are highly significant ($p < 0.01$).

Face validity. Table 8 reports reasonable values for the average WTP for various quantities. For example, WTP for 40 hours of Internet access ranges between 18.75 and 37.14 Euros, whereas that for 80 hours ranges between 23.13 and 45.39 Euros. However, contingent valuation leads to relatively low WTP values. Additionally, Table 9 indicates significant correlations (except in one case) between the saturation level of the estimated WTPF and the maximum usage reported by the respondents. Furthermore, the differences between the saturation level of the estimated WTPF and reported maximum Internet usage are mostly insignificant. These results support the face validity of all methods.

Internal validity. We calculate the correlation coefficients between the actual and the predicted rank of the stimuli (i.e., ranking-based conjoint task) and the hit rate for the actual and predicted choices (i.e., choice-based conjoint task) on the basis of the estimated WTPF parameters and thus analyze the internal validity of the three methods. The Spearman correlation coefficient varies between 0.74 and 0.93, and the hit rate ranges between 0.56 and 0.83. Choice-based conjoint analysis achieves the highest hit rate, whereas ranking-based conjoint analysis earns highest correlation between actual and predicted rankings. The corresponding results for contingent valuation are lowest for both measures. Thus, contingent valuation performs much worse than either form of conjoint analysis.

Predictive validity. Similar to Study 1, we use the five holdout choice sets to analyze the predictive validity of our approach. The results in Table 9 indicate that ranking-based and choice-based conjoint analysis have comparably good hit rates for predicting the service purchase (85.5% and 82.1%, respectively, which exceeds the proportional chance criterion of 77%), whereas contingent valuation performs much worse with a hit rate of 65.6%. In the case of tariff choice, conjoint analyses again perform better than contingent valuation (65.5%

and 60.7% compared with 40.6%) and exceed the proportional chance criterion of 55%. We obtain similar results with regard to the usage prediction – higher correlation coefficients emerge between the self-reported and the predicted usage for conjoint analyses than for contingent valuation. Finally, there are no significant differences between the average self-reported and predicted usage for either conjoint analysis. The results show that contingent valuation leads to less valid willingness-to-pay functions.

Table 9. Face, internal, and predictive validity.

| | Ranking-based conjoint analysis | Choice-based conjoint analysis | Contingent valuation |
|--|------------------------------------|-----------------------------------|-------------------------|
| Feasibility | | | |
| Difficulty | 3.01 | 2.89 | 2.77 |
| Time (sec) | 250.94 | 208.66 | 143.15 |
| Face validity | | | |
| Correlation between reported maximum usage and predicted saturation levels | 0.43*** | 0.13 | 0.15*** |
| Internal validity | | | |
| Spearman's correlation coefficient | 0.93 | 0.86 | 0.74 |
| Hit rate | 0.64 | 0.83 | 0.56 |
| Predictive validity | | | |
| Purchase hit rate | 85.5% | 82.1% | 65.6% |
| Tariff choice hit rate | 65.5% | 60.7% | 40.6% |
| Usage (correlation) | 0.24*** | 0.23*** | 0.15*** |
| Usage (average predicted quantity in h) | 79.43 ^a | 88.77 ^a | 66.29 ^b |

* Significant at $p = 0.10$, ** Significant at $p = 0.05$, *** Significant at $p = 0.01$.

^a – Not significantly different from the average self-reported usage of 79.48 hours per month ($p < 0.05$).

^b – Significantly different from the average self-reported usage of 79.48 hours per month ($p < 0.05$).

We also build on the idea proposed by Iyengar et al. (2007) and compare our results with those of a standard conjoint analysis. They show that the standard conjoint approach performs equally well in predicting service purchase decisions (85.8% ranking-based conjoint, 81.5% choice-based conjoint) but worse in predicting the tariff choice decision (60.0% ranking-based conjoint, 57.6% choice-based conjoint). However, standard conjoint analysis does not allow for predicting different usages across tariffs. Thus, our results confirm those of Iyengar et al. (2007); namely, standard conjoint analysis is not appropriate for predicting choice and usage decisions in multiple-unit products.

8. Conclusions

We propose augmented methods of conjoint analysis to estimate willingness-to-pay functions. These functions express the amount that consumers are willing to pay for a given quantity and thereby enable us to capture a different WTP for each quantity unit of a product. We show that our methods allow for the simultaneous prediction of consumers' service purchase decision, tariff choice decision, and usage quantity decision and detail how these predictions allow for analyzing the effect of price changes on market size, market volume, and market value. They also provide a means to decompose the effect of price changes into market extension, switching, and cannibalization effects, which is necessary to determine optimal nonlinear pricing structures, such as the menus of two-part tariffs used frequently for pricing services. The results of our market simulation show that changes in the fixed fee and marginal price of two-part tariffs have fairly different effects on consumers' behavior.

Our empirical study shows that the indirect elicitation format (i.e., comparison of tariffs with different fixed fees and marginal prices) leads to results with higher face, internal, and predictive validities than those of the direct elicitation format (i.e., comparison of quantity and bill amount combinations). Furthermore, the augmented methods of ranking-based and choice-based conjoint analysis for estimating WTPF lead to fairly similar results, with a slightly higher face and predictive validity for ranking-based conjoint. This result confirms the findings of previous studies that reveal rather moderate differences between different conjoint analyses (e.g., Elrod et al. 1992; Moore 2004). Contingent valuation, though argued to be easier than conjoint analysis, leads to a substantially lower validity.

Future research might extend our results in several directions. First, we do not consider tariff-specific preferences. Lambrecht and Skiera (2006) show that consumers tend to prefer flat-rate tariffs over pay-per-use tariffs, even if they have to pay more. Strong preferences for tariffs would require an estimation of tariff-specific parameters. Second, we neglect the effect of income and network externalities, which could be important topics for future studies. In particular, the latter might be relevant for services that use interactive media, including instant messaging or online dating. Third, we do not use any individual-specific stimuli but instead randomly assign each consumer to one of the two given sets of stimuli. Although the results from the two sets of stimuli are similar, generating individual-specific stimuli might offer an even better method for estimating the parameters of the WTPF. Moreover, we do not provide any additional information to respondents that would have let them compare the stimuli more effectively, such as information about the quantities that would cause the two

different tariffs to result in similar bill amounts. This information might make the ranking task easier but also would require a software-based approach to elicit the stimuli rankings.

References

- Ben-Akiva, M., Bradley, M. D., Morikawa, T., Benjamin, J., Novak, T. P., Oppewal, H., & Rao, V. (1994). Combining Revealed and Stated Preferences Data. *Marketing Letters*, 5(4), 335-350.
- Bettman, J. R., John, D. R., & Scott, C. A. (1986). Covariation Assessment by Consumers. *Journal of Consumer Research*, 13(3), 316-326.
- Brown, S. J., & Sibley, D. S. (1986). *The Theory of Public Utility Pricing* (1 ed.). Cambridge et al.: Cambridge University Press.
- Cameron, T. A., & James, M. D. (1987). Estimating Willingness to Pay from Survey Data: An Alternative Pre-Test-Market Evaluation Procedure. *Journal of Marketing Research*, 24(November), 389-395.
- Comscore. (2006). 694 Million People Currently Use the Internet Worldwide According To comScore Networks. Press Release, URL: <http://www.comscore.com/press/release.asp?press=849>, retrieved on 29.06.2006.
- Danaher, P. J. (2002). Optimal Pricing of New Subscription Services: Analysis of a Market Experiment. *Marketing Science*, 21(2), 119-138.
- Darmon, R. Y., & Rouzies, D. (1994). Reliability and Internal Validity of Conjoint Estimated Utility Functions under Free versus Error-Full Conditions. *International Journal of Research in Marketing*, 11(5), 465-476.
- Diamond, P. A., & Hausman, J. (1994). Contingent Valuation: Is Some Number Better than No Number. *Journal of Economic Perspectives*, 8(4), 45-64.
- Ding, M. (2007). An Incentive-Aligned Mechanism for Conjoint Analysis. *Journal of Marketing Research*, 44(2), 214-223.
- Elrod, T., Louviere, J. J., & Davey, K. S. (1992). An Empirical Comparison of Rating-Based and Choice Based Conjoint Models. *Journal of Marketing Research*, 29(3), 368-377.
- Green, P. E., & Srinivasan, V. (1990). Conjoint Analysis in Marketing: New Developments With Implications for Research and Practice. *Journal of Marketing*, 54(October), 3-19.
- Hagerty, M. R., & Srinivasan, V. (1991). Comparing the Predictive Powers of Alternative Multiple Regression Models. *Psychometrika*, 56(11), 77-85.
- Iyengar, R., Jedidi, K., & Kohli, R. (2007). A Conjoint Approach to Multi-Part Pricing. *Journal of Marketing Research*, forthcoming.

- Jedidi, K., & Zhang, Z. J. (2002). Augmenting Conjoint Analysis to Estimate Consumer Reservation Price. *Management Science*, 48(10), 1350-1368.
- Kalish, S., & Nelson, P. (1991). A Comparison of Ranking, Rating and Reservation Price Measurement in Conjoint Analysis. *Marketing Letters*, 2(4), 327-335.
- Kohli, R., & Mahajan, V. (1991). A Reservation-Price Model for Optimal Pricing of Multiattribute Products in Conjoint Analysis. *Journal of Marketing Research*, 28(August), 347-354.
- Kridel, D. J., Lehman, D. E., & Weisman, D. L. (1993). Option Value, Telecommunication Demand, and Policy. *Information Economics and Policy*, 5(2), 125-144.
- Lambrecht, A., Seim, K., & Skiera, B. (2006). Does Uncertainty Matter? Consumer Behavior under Three-Part Tariffs. *Marketing Science*, forthcoming.
- Lambrecht, A., & Skiera, B. (2006). Paying Too Much and Being Happy About It: Causes and Consequences of Tariff-Choice Biases. *Journal of Marketing Research*, 43(2), 212-223.
- Mitchell, B. M., & Carson, R. T. (1989). *Using Survey to Value Public Goods: The Contingent Valuation*. Washington D.C.
- Moore, W. L. (2004). A Cross-Validity Comparison of Ratings-Based and Choice-Based Conjoint Analysis Models. *International Journal of Research in Marketing*, 21(3), 299-312.
- Oren, S. S., Smith, S. A., & Wilson, R. B. (1982). Nonlinear Pricing in Markets with Interdependent Demand. *Marketing Science*, 1(3), 287-313.
- Srinivasan, V. (1982). Comments of the Role of Price in Individual Utility Judgment. In J. Sheth (Ed.), *Choice Models for Buying Behavior, Research in Marketing Supplement 1*. Greenwich: JAI Press.
- Swait, J., Erdem, T., Louviere, J., & Dubelaar, C. (1993). The Equalization Price: A Measure of Consumer-Perceived Brand Equity. *International Journal of Research in Marketing*, 10(1), 23-45.
- Train, K. E., McFadden, D. L., & Ben-Akiva, M. (1987). The Demand for the Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *Rand Journal of Economics*, 18(1), 109-123.
- Voelckner, F. (2006). An Empirical Comparison of Methods for Measuring Consumers' Willingness to Pay. *Marketing Letters*, 17(2), 137-149.

- Wang, T., Venkatesh, R., & Chatterjee, R. (2007). Reservation Price as a Range: An Incentive-Compatible Measurement Approach. *Journal of Marketing Research*, 44(2), 200-213.
- Wertebroch, K., & Skiera, B. (2002). Measuring Consumers' Willingness to Pay at the Point of Purchase. *Journal of Marketing Research*, 39(2), 228-241.
- Wilson, R. (1993). *Nonlinear Pricing*. New York: Oxford University Press.

The Influence of Tariff-Specific Preferences on Tariff Choice and Usage

Agnieszka Wolk

Anja Lambrecht

Bernd Skiera

Wolk, A., Lambrecht, A., and Skiera, B. (2005). The Influence of Tariff-Specific Preferences on Tariff Choice and Usage Price Elasticities. Working Paper, University of Frankfurt.

The Influence of Tariff-Specific Preferences on Tariff Choice and Usage

Abstract

For many services, consumers can choose among a range of optional tariffs that differ in their access and usage prices. Recent studies indicate that tariff-specific preferences may lead consumers to choose a tariff that does not minimize their expected bill. This study analyzes how tariff-specific preferences influence the responsiveness of consumers' usage and tariff choice to changes in prices. We show that consumer heterogeneity in tariff-specific preferences lead to heterogeneity in their sensitivity to price changes. Specifically, consumers with tariff-specific preferences are less sensitive to price increases of their preferred tariff than other consumers. Our results provide an additional reason why firms should offer multiple tariffs rather than a uniform nonlinear pricing plan to extract maximum consumer surplus.

Keywords: nonlinear pricing, tariff choice, tariff-specific preferences, price elasticity, flat-rate, three-part tariff.

1. Introduction

For many services, such as telecommunication or online information, consumers can choose between a large number of optional pricing plans, including flat rates, pay-per-use tariffs, or two- and three-part tariffs. Because consumers' tariff choice affects their usage, the bill, and the company's profits, setting optimal prices is of great importance. Yet companies often experiment with different pricing schemes at great cost (Essegaier et al. 2002).

Standard economic theory assumes that a consumer chooses a tariff that minimizes the bill given his expected usage. However, empirical studies suggest that consumers base their tariff choices not only on the expected bill but also on tariff-specific preferences. For example, consumers may prefer a flat rate tariff to usage-based pricing (Lambrecht and Skiera 2006; Nunes 2000; Train et al. 1987). If tariff-specific preferences influence a consumer's tariff choice, such preferences should also affect his price sensitivity. However, most studies on tariff choice neglect the influence of tariff-specific preferences on price responsiveness assuming that consumers are homogeneous in their price sensitivity (Kling and van der Ploeg 1990; Lambrecht et al. 2007; Lee 1999; Train et al. 1987). This may prompt suboptimal pricing strategy recommendations (Gensch 1985).

The aim of this paper is to analyze how tariff-specific preferences influence the responsiveness of consumers' tariff choice and usage to price changes. In doing so, we aim to add to researchers' and managers' understanding of consumers' tariff choice and ultimately help to improve pricing decisions. We use attitudinal data to segment consumers by tariff-specific preferences and then exploit usage data to analyze how those preferences influence price elasticities, a common measure of price sensitivity (Kaul and Wittink 1995). A key feature of our approach is that we combine actual usage data with attitudinal data of the same consumers.

The paper is organized as follows: We first discuss related literature and introduce a conceptual model of the effect of tariff-specific preferences on tariff choice and usage. Next, we demonstrate how to empirically measure consumers' tariff choice and usage decisions when accounting for tariff-specific preferences. We then present our empirical study and results. We conclude with a discussion of the implications of our study.

2. Literature review

With a flat-rate tariff, consumers pay only an access price, whereas pay-per-use tariffs charge only a usage price. In a two-part tariff, consumers pay both an access price for obtaining

access to the service and a usage price for the quantity used. In a three-part tariff, consumers obtain a usage allowance for paying the access price, for example free minutes on a cell phone plan, and then pay a usage price only when their usage exceeds the allowance.

It is often assumed that when choosing among menus of those tariffs, consumers prefer the tariff that minimizes their bill, given their expected usage (Brown and Sibley 1986; Iyengar et al. 2007). Yet, recent studies indicate that many consumers choose a tariff that does not minimize their bill but are subject to a flat-rate bias: Those consumers select a flat rate or a tariff with a higher allowance even though they would pay less on a tariff that charges for actual usage. Alternatively, they may choose a tariff that charges for actual usage even though they would pay less on a flat rate (pay-per-use bias) (see among others Lambrecht and Skiera 2006; Miravete 2002; Nunes 2000; Train et al. 1987). These results suggest that, in addition to bill, choice of tariffs is also driven by consumers' preferences for tariff-specific characteristics, such as a high allowance.

Previous findings (Kling and van der Ploeg 1990; Lambrecht and Skiera 2006; Miravete 2002; Prelec and Loewenstein 1998; Train 1991) suggest three causes of why consumers may prefer flat rates: to insure against the risk of high costs in periods of higher-than-average usage (insurance effect); to enjoy their usage more, because the usage is not metered and the bill does not increase with usage (taxi meter effect); or to avoid the burdensome effort of comparing alternative tariffs (convenience effect). Lambrecht and Skiera (2006) can, however, not confirm that the convenience effect leads to a flat-rate bias. Other potential drivers that may steer consumers toward tariffs that are not optimal ex-post include their overestimation of usage (Nunes 2000) or uncertainty about future demand when they make a tariff choice (Lambrecht et al. 2007). These drivers result from consumers' cognitive ability and usage characteristics and as such do not reflect preferences for tariffs.

Marketing research provides ample evidence that attitudes guide behavior (e.g., Fazio and Zanna 1981). Consequently, we should also expect a consumer's tariff-specific preferences to affect his price sensitivity with respect to tariff choice and usage. There is, however, little research on the effect of tariff-specific preferences on consumers' price sensitivity. Below, we develop a framework that illustrates the effect of tariff-specific preferences on price sensitivity.

3. Conceptual model

3.1. Influence of tariff-specific preferences on price sensitivity with respect to tariff choice

When selecting a tariff, the expected bill is not the only choice criterion for consumers who care about the tariff's characteristics (e.g., the constant bill of a flat rate). Consequently, we expect such consumers to be less sensitive to a price increase of their preferred tariff than consumers whose choice is exclusively guided by the expected bill (for a similar argument in the context of brand choice, see Lichtenstein et al. 1990). Similarly, we expect consumers who dislike characteristics of a given tariff to be more responsive to price increases of this tariff.

In line with previous findings we define three segments of consumers: (1) Consumers that have a preference for flat rates, (2) consumers whose choice is not affected by tariff-specific characteristics, and (3) consumers who dislike the characteristics of flat rates, which we will refer to as a flat-rate aversion. We expect consumers who prefer flat-rate tariffs to be less sensitive to increases in the access price of flat-rate tariffs, and more generally less sensitive to increases in the access and usage price of tariffs that share similar characteristics with flat rates (e.g., three-part tariffs with high usage allowances) than other consumers. Conversely, such consumers should be more sensitive to increases in usage price of pay-per-use tariffs, and more generally more sensitive to increases in the access and usage price of tariffs that have none or only a small usage allowance. We anticipate the opposite effect for consumers with a flat-rate aversion. We consequently expect price sensitivities to vary across segments as illustrated in Table 1.

Table 1. Price sensitivity expectations with respect to tariff choice.

| Tariff | Tariff description | Access price elasticity | | | Usage price elasticity | | |
|----------|---------------------------------------|----------------------------|-----------------------------|------------------------------|----------------------------|-----------------------------|------------------------------|
| | | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment |
| Tariff 1 | Three-part tariff with low allowance | Low | Middle | High | Low | Middle | High |
| Tariff 2 | Three-part tariff with high allowance | Middle | Middle | Middle | High | Middle | Low |
| Tariff 3 | Flat rate | High | Middle | Low | | | |

3.2. Influence of tariff-specific preferences on price sensitivity with respect to usage

Companies aiming to set optimal prices need to understand how prices affect tariff choice as well as usage. Under optional tariffs, the usage price enters a demand function that is conditional on tariff choice (Brown and Sibley 1986; Train et al. 1987) and, thus, has a direct effect as well as an indirect effect on usage via its influence on tariff choice. The access price indirectly influences usage through its effect on tariff choice. We discuss the effect of access and usage price in turn.

Access price

In response to increasing the access price of a flat rate or a three-part tariff with a high allowance consumers with a flat-rate aversion are more likely than other consumers to switch down to a tariff with a lower access price, a lower usage allowance, or a higher usage price (Lambrecht et al. 2007; Train et al. 1987). Because these switchers face a higher marginal price, their expected usage is likely to decrease. In sum, an increase of the access price of a tariff with a high access price and allowance decreases usage of consumers with a flat-rate aversion more than of consumers with a flat-rate preference simply because the latter are less likely to switch tariffs.

Further, if the company increases the access price of a tariff with a low usage allowance, consumers of that tariff are likely to switch up to a tariff with a higher allowance or lower usage price. Switchers thus face a lower marginal price, resulting in a higher expected usage. On average, the effect of an increase in access price of a tariff with a low usage allowance on usage is strongest for consumers with a flat-rate preference as they are more likely to switch up to a tariff with a higher access price, a higher usage allowance or a lower usage price, and lowest for consumers with a flat-rate aversion.

Usage price

Determining the effect of changes in usage prices on usage is less obvious. An increase in the usage price reduces the usage of those consumers who stay on the same tariff. Yet, an increase in the usage price might also induce consumers to switch up to tariffs with a higher access price, a higher usage allowance or a lower usage price, which would increase their usage. We expect a high negative effect of a price increase on usage for consumers that have a flat-rate aversion and are less likely to switch up to tariffs with higher allowances than for consumer that have a flat-rate preference. The latter are more likely to switch up to a tariff

with a higher access price or a higher allowance. Therefore, we expect a positive effect for them. Table 2 summarizes the effects. We next aim to empirically validate differences in price sensitivities across segments.

Table 2. Price sensitivity expectations with respect to usage.

| Tariff | Tariff description | Access price elasticity | | | Usage price elasticity | | |
|----------|---------------------------------------|----------------------------|-----------------------------|------------------------------|----------------------------|-----------------------------|------------------------------|
| | | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment |
| Tariff 1 | Three-part tariff with low allowance | Positive low | Positive middle | Positive high | Negative high | Negative middle | Positive high |
| Tariff 2 | Three-part tariff with high allowance | Negative middle | Negative low | Positive middle | Negative middle | Negative low | Positive middle |
| Tariff 3 | Flat rate | Negative high | Negative middle | Negative low | | | |

4. Methodology

Previous literature finds that two attitudinal effects influence tariff-specific preferences: the taxi meter and the insurance effect (Lambrecht and Skiera 2006). We use the same multi-item scales as in Lambrecht and Skiera (2006) to identify consumers with (1) a flat-rate preference, (2) a flat-rate aversion, and (3) tariff indifference. Consumers that score 4 or higher on the 5-point Likert scale for either the taxi meter effect or the insurance effect, and as such agree or strongly agree to have a preference for a flat rate, are assigned to the flat-rate preference segment. Consumers who score 2 or lower on both scales are classified as the flat-rate aversion segment. The remaining consumers constitute the segment that is indifferent between tariff-specific characteristics.

We use transactional data from an Internet provider to model consumers' usage and tariff choice decisions. The challenge is to account for the interdependency between tariff choice and usage. We follow Train et al. (1987) and Lee (1999) and estimate a nested logit model in which consumer i chooses a usage portfolio p that reflects the amount of Internet usage. This portfolio is defined by the number of logins to the Internet per month (N) and the average data volume transferred per login (V). Conditional on the chosen usage portfolio p , consumer i chooses tariff t . The probability P_{pti} that consumer i chooses a usage portfolio p and tariff t is:

$$(1) P_{pti} = \frac{\exp(U_{pti}) \left(\sum_T \exp(U_{pTi})^{\lambda-1} \right)}{\sum_P \sum_T \exp(U_{pTi})^\lambda},$$

where U_{pti} is consumer i 's utility of choosing usage portfolio p and tariff t . We can rewrite the probability P_{pti} as a product of the marginal probability that consumer i chooses the usage portfolio p , P_{pi} , and the conditional probability that he chooses tariff t given usage portfolio p , $P_{t/pi}$, as follows:

$$(2) P_{pti} = P_{pi} P_{t/pi}.$$

We further define the marginal probability that consumer i chooses usage portfolio p as follows:

$$(3) P_{p/Bi} = \frac{\exp(\phi \log N_{pi} V_{pi} - \alpha N_{pi} + \lambda I_{ti} + \ln P(B/p))}{\sum_B \exp(\phi \log N_{pi} V_{pi} - \alpha N_{pi} + \lambda I_{ti} + \ln P(B/p))},$$

Where $\log N_{pi} V_{pi}$ represents benefits of Internet usage, N_{pi} represents opportunity costs of time for every login to the Internet, I_{ti} is the inclusive value of tariff t , and $\ln P(B/p)$ corrects for the bias that results from using a sample B of immense usage portfolios for each household (for details, see Lee 1999; Train et al. 1987).

The choice of the tariff depends on the consumer's bill for this tariff, conditional on the choice of usage portfolio B_{pti} . Consequently, we define consumer i 's conditional probability of choosing tariff t given usage portfolio p as:

$$(4) P_{t/pi} = \frac{\exp(\beta_{1t} + \beta_2 B_{pti})}{\sum_T \exp(\beta_{1t} + \beta_2 B_{pTi})}.$$

5. Data

We use attitudinal and transactional data of consumers of a German Internet service provider (for more details, see Lambrecht and Skiera 2006). The provider offered three different tariffs in 2003: (1) Tariff 1, a three-part tariff with a low access price and a low monthly allowance; (2) Tariff 2, a three-part tariff with a higher access price and a higher allowance than Tariff 1 but the same usage price; and (3) Tariff 3, a flat rate with unlimited usage. The data includes

the tariff choice and the monthly usage measured in megabyte for 11,745 customers over a time period of up to five months in 2003, a total of 49,107 monthly usage observations.

Information about latent attitudes comes from an online survey conducted among a representative sample of customers of the Internet service provider. The survey consists of items that measure the taxi meter and insurance effects on a 5-point Likert scale (1 - strongly disagree, 5 - strongly agree) (Lambrecht and Skiera 2006). From the sample of 12,000 customers, we obtain 1,078 complete responses. For 941 consumers we match the transactional data to the survey data which constitutes our final sample with 3,910 monthly observations.

6. Results

6.1. Measurement of constructs

The results of the confirmatory factor analysis indicate good overall model fit: χ^2/df 3.19, root mean square error of approximation 0.05, goodness-of-fit index 0.99, adjusted goodness-of-fit index 0.98, normed fit index 0.99, Tucker-Lewis index 0.98, and confirmatory fit index 0.99. The individual factors have coefficient alphas of 0.80 and 0.58, construct reliabilities of 0.81 and 0.65, and variance extracted estimates of 0.51 and 0.51 for the taxi meter and insurance effects, respectively. All measures for scale reliability exceed critical values. Except for two, all item reliabilities exceed 0.4, and all t-values for factor loadings exceed 10.0 ($p < 0.01$). All corrected item-to-total correlations are greater than 0.40.

6.2. Segmentation of customers

As laid out in section 3, we divide our sample into three groups based on survey results: (1) a flat-rate preference segment, (2) a flat-rate aversion segment, and (3) a tariff indifference segment. 49% of consumers have a flat-rate preference, 7% a flat-rate aversion, and 43% belong to the tariff indifferent segment. These results are similar to the findings of Prelec and Loewenstein's (1998).

6.3. Results of tariff choice model

Table 3 presents the results of different tariff choice models.⁴ Model 1 is based on the full sample. Models 2 and 3 refer to the subset of consumers who participated in the survey. Model 3 also accounts for tariff-specific preferences. The similar pattern across models 1 and 2 confirms that our subset of consumers is representative. A comparison of models 2 and 3 shows that accounting for tariff-specific preferences improves model fit. The likelihood ratio test shows a significant increase in loglikelihood when we segment consumers according to their tariff-specific preferences and rejects the hypothesis of equal response parameters between segments ($LR = 43,858.07 > \chi_{12;0.95}^2 = 21.03$). Model 3 also has greater explanatory power than model 2 ($R^2 = 0.21$ compared with 0.14).

We focus on the results of model 3. As expected, the bill decreases tariff choice probabilities, an effect that is most pronounced for the flat-rate aversion segment ($\beta_2 = -0.16$). The results with respect to the choice of a usage portfolio are in line with our expectations: Benefits from using the Internet increase, whereas opportunity costs decrease the probability of choosing a given usage portfolio. The coefficient of the inclusive value for the flat-rate preference and flat-rate aversion segments is greater than 1 ($\lambda = 1.42$ and $\lambda = 1.03$, respectively). This indicates that consumers who like or dislike tariff-specific characteristics respond to changes in the bill more readily by adjusting their usage rather than by switching their tariff. By contrast, consumers who are indifferent between tariffs switch tariffs more easily than usage levels, as indicated by a coefficient of the inclusive value below 1 ($\lambda = 0.98$ for tariff indifference segment). These patterns are consistent with our expectations: Consumers who prefer a certain type of tariff are more likely to keep that tariff and adjust their usage than to switch to a different tariff in response to price changes. In contrast, consumers with no tariff-specific preferences find it easier to switch in case of a price change.

⁴ To check the stability of our results, we use another segmentation rule. Consumers that score 4 and higher on both the taxi meter effect and insurance effect measures are classified to the flat-rate preference segment, those who score 2 or lower on both measures are classified to the flat-rate aversion segment, and the remainders are classified to the indifferent segment. According to this rule, the size of the flat rate preference segment decreases from 49% to 17%, and the size of a tariff indifference segment increases from 43% to 76%, while the flat-rate aversion segment does not change. The results provide a consistent pattern for both segmentation rules used.

Table 3. Results from model estimation.

| | Model 1 | Model 2 | Model 3 | | |
|-------------------------------------|-------------|------------|----------------------------|-----------------------------|------------------------------|
| | | | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment |
| Tariff choice | | | | | |
| Intercept tariff 1 (β_{11}) | 1.70*** | 2.05*** | 2.93*** | 4.21*** | 1.58*** |
| Intercept tariff 2 (β_{12}) | 0.64** | 1.86*** | 0.70 | 2.90*** | 1.61*** |
| Bill (β_2) | -0.09*** | -0.06*** | -0.16*** | -0.10*** | -0.05*** |
| Portfolio choice | | | | | |
| Benefit (ϕ) | 0.26*** | 0.33*** | 0.45*** | 0.39*** | 0.34*** |
| Cost (α) | 0.0002** | 0.002*** | 0.006*** | 0.004*** | 0.001*** |
| Inclusive value (λ) | 1.10*** | 1.19*** | 1.03*** | 0.98*** | 1.42*** |
| Loglikelihood | -138,796.40 | -11,423.97 | | | -10,505.07 |
| Number of Par. | 6 | 6 | | | 18 |
| Observations | 49,023 | 3,910 | | | 3,910 |
| R ² | 0.10 | 0.14 | | | 0.21 |
| Segment size | | | 287 7.34% | 1,698 43.43% | 1,925 49.23% |

*** Significant at p = 0.01, ** Significant at p = 0.05, * Significant at p = 0.10.

6.4. Elasticities of tariff choice

Based on the parameter estimates we compute the price elasticities of tariff choice per segment (percentage change in choice divided by the percentage increase in access or usage price). All elasticities have the expected negative sign, but clearly differ by segment (see Table 4). Consumers with tariff-specific preferences tend to be less sensitive to price increases of their preferred tariff than other segments. Specifically, consumers who prefer flat-rate tariffs are less sensitive to an increase in the access price of the flat rate than consumers with a flat-rate aversion (-0.85 versus -1.62). These results imply that consumers with a flat-rate preference are less likely to switch down to a three-part tariff in case of an increase of the access price of a flat rate than consumers with a flat-rate aversion. Further, consumers with a flat-rate aversion are least sensitive to an increase of the access and usage price of tariff 1 which is the tariff with the lowest allowance (-0.04 and -0.03 for access and usage price in case of flat-rate aversion segment compared to -0.16 and -0.10 for access and usage price in case of flat-rate preference segment). These results suggest that flat-rate averse consumers who face an increase of the access and usage price of a three-part tariff with a low allowance are more likely to stay with this tariff than consumers with a flat-rate preference.

Table 4. Relative price elasticities of tariff choice.

| Tariff | Tariff description | Access price elasticity | | | Usage price elasticity | | |
|----------|--|----------------------------|-----------------------------|------------------------------|----------------------------|-----------------------------|------------------------------|
| | | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment |
| Tariff 1 | Three-part tariff with low access price and allowance | -0.04 | -0.09 | -0.16 | -0.03 | -0.08 | -0.10 |
| Tariff 2 | Three-part tariff with high access price and allowance | -1.61 | -1.00 | -0.40 | -0.06 | -0.05 | -0.03 |
| Tariff 3 | Flat rate | -1.62 | -1.23 | -0.85 | | | |

6.5. Elasticities of usage

Table 5 shows the price elasticities of usage. The differences between segments indicate that tariff-specific preferences also influence how consumers' usage responds to price increases. An increase of the access price of tariff 1 has the greatest positive effect on usage in the flat-rate preference segment as these consumers are most likely to switch up to a tariff with a greater allowance (elasticity in the flat-rate preference segment is 0.09, compared to 0.07 in the flat-rate aversion segment). Increasing the access price of tariff 2 decreases usage among consumers with a flat-rate aversion (price elasticity -0.12) that are likely to switch down to tariff 1 but increases usage among customers with a preference for a flat-rate tariff (price elasticity 0.08), that have a high probability to switch up to a flat rate. Finally, the increase in the access price of a flat-rate tariff decreases usage in all segments, with the highest effect in the flat-rate aversion segment (-0.53 in the flat-rate aversion segment compared to -0.05 in the flat-rate preference segment).

We turn to the usage price sensitivity. An increase in the usage price has a stronger negative effect in the flat-rate aversion segment (-0.25 and -0.08) than in the flat-rate preference segment (-0.06 and -0.01). This stronger negative effect in the flat-rate aversion segment occurs because this segment is less likely to switch up to tariffs with a higher allowance or usage price. These consumers stay on their current tariff and decrease their usage. While the negative values in the flat-rate preference segment are inconsistent with our proposition, the results still support our expectation that in the flat-rate preference segment the high extent of switching to a flat rate compensates for changes in the usage of customers who remain in tariffs 1 and 2.

Table 5. Elasticities of usage.

| Tariff | Tariff description | Access price elasticity | | | Usage price elasticity | | |
|----------|---|----------------------------|-----------------------------|------------------------------|----------------------------|-----------------------------|------------------------------|
| | | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment | Flat-rate aversion segment | Tariff indifference segment | Flat-rate preference segment |
| Tariff 1 | Three-part tariff with low allowance (small tariff) | 0.07 | 0.08 | 0.09 | -0.25 | -0.20 | -0.06 |
| Tariff 2 | Three-part tariff with high allowance | -0.12 | -0.14 | 0.08 | -0.08 | -0.04 | -0.01 |
| Tariff 3 | Flat rate (big tariff) | -0.53 | -0.04 | -0.05 | | | |

7. Conclusions and implications

Despite recent studies that indicate heterogeneity in consumers' tariff-specific preferences, most research on tariff choice assumes that consumers are homogenous in their tariff choice and price sensitivity. We address this limitation and analyze the extent of tariff-specific preferences and their influence on consumers' price elasticity of tariff choice and usage.

The results show that accounting for tariff-specific preferences when modeling tariff choice significantly improves the model fit. Further, we show that tariff-specific preferences influence consumers' price sensitivity with respect to both tariff choice and usage. Consumer's tariff choice is less sensitive to price increases of their preferred tariff. More specifically, consumers with a flat-rate preference are relatively insensitive to increases in the access and the usage price of tariffs that have a high or unlimited usage allowance. By contrast, consumers with a flat-rate aversion are relatively insensitive to increases in the access and usage prices of tariffs with a low usage allowance. Likewise, we find heterogeneity in how consumers' usage responds to price changes: Increasing the usage price has a strong negative effect on usage in the flat-rate aversion segment and only a moderate negative effect in the flat-rate preference segment. The latter segment is more likely to switch up to a tariff with a higher allowance. On the other hand, increasing the access price of a tariff with a low allowance may increase usage. This effect is greatest in the flat-rate preference segment. Those consumers are more likely to switch up to tariffs with greater allowances where they are more likely to face a marginal price of zero. Our results show that a company can use prices to steer consumers' tariff choice and thus their usage. Likewise, a policy maker may consider price regulation that fosters socially approved behavior.

Finally, we find that when facing a price increase, consumers with tariff-specific preferences are more likely to adjust their usage, whereas consumers with no tariff-specific preferences more likely adjust their tariffs. These results complement existing studies. Whereas Iyengar (2005) argues that consumers actively try to control their usage costs by either switching tariffs or adjusting their consumption patterns, other studies report tariff stickiness (Lee 1999; Train et al. 1987). Our results demonstrate that this heterogeneity in observed switching behavior may be caused by tariff-specific preferences.

Our findings on the effect of tariff-specific preferences on price elasticities have implications for firms offering multiple optional tariffs. Heterogeneous service valuations constitute a necessary condition for a uniform nonlinear pricing plan. When consumers have heterogeneous preferences for tariffs, firms can better segment consumers and extract greater consumer surplus by offering multiple optional pricing plans. These results are in line with market trends in service industries: In recent years, many service providers increased the number of optional tariffs. For example, the German cell phone service provider E-Plus more than doubled the number of optional tariffs, from 12 in 2000 to 28 in 2004.

References

- Brown, S. J., & Sibley, D. S. (1986). *The Theory of Public Utility Pricing*. Cambridge et al.: Cambridge University Press.
- Essegaier, S., Gupta, S., & Zhang, Z. J. (2002). Pricing Access Services. *Marketing Science*, 21(2), 139-159.
- Fazio, R. H., & Zanna, M. P. (1981). Direct Experience and Attitude-Behavior Consistency. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology* (Vol. 14, pp. 162-202). New York: Academic Press.
- Gensch, D. H. (1985). Empirically Testing a Disaggregate Choice Model for Segments. *Journal of Marketing Research*, 22(4), 462-467.
- Iyengar, R. (2005). A Structural Demand Analysis for Wireless Services under Nonlinear Pricing Schemes. Working Paper, Columbia University.
- Iyengar, R., Jedidi, K., & Kohli, R. (2007). A Conjoint Approach to Multi-Part Pricing. *Journal of Marketing Research*, forthcoming.
- Kaul, A., & Wittink, D. R. (1995). Empirical Generalizations about the Impact of Advertising on Price Sensitivity and Price. *Marketing Science*, 14, G151-G160.
- Kling, J. P., & Ploeg, S. S. v. d. (1990). Estimating Local Elasticities with a Model of Stochastic Class of Service and Usage Choice. In A. d. Fontenay & M. H. Shugard & D. S. Sibley (Eds.), *Telecommunications Demand Modelling. An Integrated View*. Amsterdam: North Holland.
- Lambrecht, A., & Skiera, B. (2006). Paying Too Much and Being Happy About It: Causes and Consequences of Tariff-Choice Biases. *Journal of Marketing Research*, 43(2), 212-223.
- Lambrecht, A., Seim, K., & Skiera, B. (2007). Does Uncertainty Matter? Consumer Behavior under Three-Part Tariffs. *Marketing Science*, forthcoming.
- Lee, B. (1999). Calling Patterns and Usage of Residential Toll Service under Self Selecting Tariffs. *Journal of Regulatory Economics*, 16(1), 45-81.
- Lichtenstein, D. R., Netemeyer, R. G., & Burton, S. (1990). Distinguishing Coupon Proneness from Value Consciousness: An Acquisition-Transaction Utility. *Journal of Marketing*, 54(3), 54-67.
- Miravete, E. (2002). Choosing the Wrong Calling Plan? Ignorance and Learning. *American Economic Review*, 93(1), 297 – 310.

- Nunes, J. (2000). A Cognitive Model of People's Usage Estimations. *Journal of Marketing Research*, 37(November), 397-409.
- Prelec, D., & Loewenstein, G. (1998). The Red and the Black: Mental Accounting of Savings and Debt. *Marketing Science*, 17(1), 4-28.
- Train, K. E. (1991). *Optimal Regulation. The Economic Theory of Natural Monopoly*. Cambridge (Mass.): MIT Press.
- Train, K. E., McFadden, D. L., & Ben-Akiva, M. (1987). The Demand for the Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *Rand Journal of Economics*, 18(1), 109-123.

**Established Phenomenon or Occasional Incident?
Persistence of Tariff-Choice Biases across Pricing
Schemes**

Agnieszka Wolk

Wolk, A. (2007). Established Phenomenon or Occasional Incident? Persistence of Tariff-Choice Biases across Pricing Schemes, under review at Schmalenbach Business Review.

Established Phenomenon or Occasional Incident? Persistence of Tariff-Choice Biases across Pricing Schemes

Abstract

Existing empirical studies show that consumers in their tariff-choice decision are not driven by the bill-minimizing rule as predicted by the standard economic theory. Often, consumers choose a more expensive tariff than necessary which indicates a tariff-choice bias. Although tariff-choice biases are well recognized in the literature, it remains unclear how persistent they are across varying pricing schemes and whether companies should account for them when designing their nonlinear pricing schemes. This paper shows that tariff-choice biases are sensitive to pricing schemes and tariff prices as well as the resulting break-even point significantly influence the probability of a tariff-choice bias occurrence. Furthermore, the results show that many consumers may be potentially willing to pay more for their favorite tariff; however, the company loses this potential profit if the pricing scheme is not adequately designed. As such, the paper underlines the importance of accounting for tariff preferences and tariff-choice biases when designing the pricing scheme. Managerial implications that allow to better skim tariff-specific willingness to pay are derived.

Keywords: nonlinear pricing, tariff choice, tariff-choice bias.

1. Introduction

Rapid growth of service industries such as wireless telecommunication, Internet access or digital goods like online music and newspapers increases also the popularity of self-selecting tariffs. Thereby, providers offer consumers a pricing scheme which consists of a set of optional tariffs and allow them to choose one tariff that best suits their usage. A simple pricing scheme can consist of at least two optional tariffs, e.g., a pay-per-use tariff where consumers are charged a marginal price for the usage and a flat rate where consumers pay a fixed fee and can consume as much as they want for this fee. Recently, two- and three-part tariffs that consist of both a fixed fee and a marginal price are gaining popularity.

According to standard economic theory a consumer facing the tariff choice should maximize his consumer surplus and choose a tariff that minimizes the bill amount given his expected usage (Skiera 1999; Tacke 1989). Nevertheless, empirical studies show that consumers not always choose the tariff that minimizes the bill amount. Consumers that choose a flat rate even though a pay-per-use tariff would lead to a lower bill are argued to have a flat-rate bias (Della Vigna and Malmendier 2005; Kling and Ploeg 1990; Nunes 2000; Schulze and Gedenk 2005; Train et al. 1987). On the other hand, consumers that choose a pay-per-use tariff even though under a flat rate they would pay less are claimed to have a pay-per-use bias (Kridel et al. 1993; Lambrecht and Skiera 2006; Miravete 2002).

The evidence for both types of biases is well documented in the literature. However, less is known about how persistent the tariff-choice biases are and whether consumers continually and repeatedly choose a wrong tariff or whether they switch to a bill-minimizing tariff. Two types of persistence can be distinguished: (1) persistence over time and (2) persistence across pricing schemes. When it comes to time-persistence the results are mixed. In their study, Lambrecht and Skiera (2006) analyze a period of 3 and 5 months and show that many consumers continuously choose a wrong tariff in every month indicating time-persistent tariff-choice biases. Conversely, other studies argue that consumers try to actively control their bills by either switching their tariff or changing their consumption patterns (Iyengar 2005; Miravete 2002).

When it comes to persistence across pricing schemes, there is no study that analyzes whether tariff-choice biases occur continuously and repeatedly under varying pricing schemes. Nevertheless, different levels of tariff-choice bias across various studies imply that they may not be persistent across pricing schemes. While some authors report that a prevalence of

consumers choose a flat rate even though the bill amount would be lower under a pay-per-use tariff (e.g., Della Vigna and Malmendier 2005; Kridel et al. 1993; Lambrecht and Skiera 2006), Miravete (2002) documents that more consumers have a pay-per-use bias rather than a flat-rate bias.

Changes in pricing scheme can have two opposite effects on the tariff-choice bias occurrence. On one hand, the low price of a flat rate makes the flat rate most favorable for more consumers while the pay-per-use tariff appears to be more favorable for a lower number of consumers. Since flat-rate bias can only be observed among consumers for whom a pay-per-use tariff is optimal, low price of a flat rate may lead to a lower occurrence of flat-rate bias. On the other hand, an attractive flat rate means that even people with a slight preference for a flat rate and hence a low additional willingness to pay for a flat rate can afford it and occurrence of a flat rate bias may increase. Similarly, two opposite effects can be observed in case of pay-per-use bias. Consequently, tariff-choice bias occurrence is likely to depend on the pricing scheme, however, net effect of pricing scheme on tariff-choice bias occurrence is difficult to predict.

The occurrence of tariff choice biases is very important for the companies. According to Lambrecht and Skiera (2006), flat-rate bias may lead to a short and long term profit increase of 141-182% and 87-135% respectively. In contrast, pay-per-use bias leads only to short term profit increase of 157-283% while in the long term it decreases the profit by 2-8% due to an increased churn rate. These results suggest that consumers have an additional willingness to pay for a flat rate that a company can skim when a flat-rate bias is observed. If the pricing scheme influences tariff-choice bias occurrence, it can be designed in order to maximize flat-rate bias occurrence to skim tariff specific willingness to pay and minimize pay-per-use bias occurrence. Therefore, it is of high interest to investigate the effect of pricing scheme on tariff choice bias occurrence. Similarly, Nunes (2000) calls for a research that would clarify the managers' abilities to manipulate tariff choice biases.

Since the existing papers focus only on one pricing scheme, they fail to observe the effect of pricing schemes on the bias occurrence. Consequently, the aim of this paper is to analyze the persistence of tariff-choice biases across varying pricing schemes. First, it is analyzed whether consumers continually choose a wrong tariff across varying pricing schemes. Two definitions of tariff-choice bias: (1) based on the usage level and break-even point (Nunes 2000) and (2) based on the consumer surplus (Kling and van der Ploeg 1990) as well as two measures of a tariff-choice bias: (1) absolute (i.e., number of respondents with a tariff-choice

bias) (Nunes 2000) and (2) conditional (i.e., number of respondents with a tariff-choice bias conditional on the tariff chosen) (Lambrecht and Skiera 2006) are used in the study. Second, the effect of tariff prices (i.e., a fixed fee and a marginal price) and break-even point on the tariff-choice bias occurrence is investigated. Third, the paper shows how a pricing scheme can be set in order to better skim consumer willingness to pay for a tariff.

Studies on tariff choice biases use two different data sources: transactional (e.g., Lambrecht and Skiera 2006; Miravete 2002) as well as survey data (e.g., Lambrecht and Skiera 2006; Nunes 2000; Schulz and Gedenk 2005). Although transactional data have higher external validity, they also have a limitation in that the real market prices vary rarely or only within a limited range (Wertenbroch and Skiera 2002). Therefore, transactional data is not suitable for analyzing the effect of varying prices on tariff-choice bias occurrence. Instead, survey data gives the possibility to analyze various price levels. Additionally, Lambrecht and Skiera (2006) who analyze tariff-choice bias based on both transactional and survey data conclude that the results of survey data are consistent with the results of transactional data. Consequently, the focus of this study is survey data.

This paper contributes both to the academic area as well as to the practice. First, it aims to further validate the regularity and robustness of tariff-choice biases. While existing studies find evidence for the phenomenon of tariff-choice biases, this paper goes one step further and analyzes how persistent this phenomenon is. Second, the paper provides an explanation for varying occurrence of tariff-choice biases in various studies. Third, the effect of pricing scheme on tariff-choice bias occurrence is quantified. Fourth, managerial implications are derived with regard to tariff-choice bias manipulation.

The remainder of the paper is organized as follows: First, the review of the existing studies in the area of tariff-choice bias is presented. Next, the discussion about the persistence of tariff-choice biases takes place followed by four empirical studies. After presenting the results, conclusions and discussion follow.

2. Literature review

Consumers have been long assumed to choose a tariff that minimizes the bill amount given their usage. Empirical studies show, however, that this assumption does not always hold in reality. Train et al. (1987) analyze tariff-choice for local telephone service and find that on average consumers prefer a flat rate as it provides the insurance against bill variation. Hobson and Spady (1988) also notice that many consumers choose a flat rate even though they would

generate a lower bill under a measured option given their low usage. The authors also find examples of customers who choose a pay-per-use tariff although a flat rate option would lead to a lower bill.

Soon after the phenomenon was recognized, the authors started quantifying the effects. Mitchell and Vogelsang (1991) analyze the results of the AT&T experiment and find that 45% of the consumers who chose an optional calling plan would be better off under a standard measured option given their low usage. Della Vigna and Malmendier (2006) show that 80% of consumers who chose a monthly flat rate for health-club visits would have paid less had they chosen a pay-per-use tariff and only 20% chose a flat rate correctly. Similarly, Kridel et al. (1993) finds that 65% of the consumers who chose a flat rate would incur a lower bill under a measured option while only 10% of consumers who chose a pay-per-use tariff would be better off under a flat rate. These results are further supported by Nunes (1999) who finds that 65% of consumers who chose a flat rate would have saved under a pay-per-use tariff, while only 10% of those who chose a pay-per-use tariff would have saved under a flat rate. In another study, Nunes (2000) finds that 87% of consumers prefer a flat rate even though they would benefit from choosing a measured option. Lambrecht and Skiera (2006) show that up to 48% of consumers choose a tariff with a higher than optimal allowance indicating a flat-rate bias. Conversely, only as much as 9% consumers showed a pay-per-use bias.

Contrary to the previous studies, Miravete (2002) finds that only 6-12% of consumers who chose a flat rate would incur a lower bill under a pay-per-use tariff compared to 62-67% that chose a pay-per-use tariff but would have saved under a flat rate. Table 1 summarizes the percentage of consumers with tariff-choice biases.

Table 1. Literature review with regard to tariff-choice biases.

| Study | Flat-rate bias occurrence | Pay-per-use occurrence |
|-----------------------------------|---------------------------|------------------------|
| Mitchel and Vogelsang (1991) | 45% | nr |
| Kridel et al. (1993) | 65% | 10% |
| | 76% | 3% |
| | 59% | 1% |
| Nunes (1999) | 59% | 1% |
| Nunes (2000) | 87% | nr |
| | 40-93% | nr |
| | 61% | nr |
| Miravete (2002) | 6-12% | 62-67% |
| Schulze and Gedenk (2005) | 17% | 8% |
| Della Vigna and Malmendier (2006) | 80% | nr |
| Lambrecht and Skiera (2006) | 18-95% | 82% |
| | 48% | 6-9% |

nr - not reported.

3. Influence of pricing scheme on tariff-choice bias occurrence

Three reasons have been proposed to explain tariff-choice biases: (1) tariff preferences, (2) cost of tariff switch, and (3) cognitive mistakes.

Tariff preferences. First, consumers may develop a positive attitude toward a tariff and as a result they may have a tendency to choose their preferred tariff when facing a tariff choice decision. Tariff preferences also imply that consumers have a specific willingness to pay for their favorite tariff irregardless of usage or bill. Prelec and Loewenstein (1998) investigate the preference for a flat rate and a pay-per-use tariff and find that on average 48% of respondents prefer a flat rate while 28% prefer a measured option. Only 20% of the respondents feel indifferent when it comes to a flat rate and a measured option.

Various effects can be responsible for developing a preference for a tariff. First, the consumers may develop a positive attitude and a preference for a flat rate as it insures against bill variation (Train et al. 1987). Under a measured option the bill varies while under a flat rate it remains constant and thus even in periods with higher usage the consumer does not have to pay more than a flat-rate fee (i.e., insurance effect). Additionally, a preference for a flat rate can be developed as consumers may enjoy the usage more when it is decoupled from payment (Prelec and Loewenstein 1998). Prelec and Loewenstein (1998) argue that mental prepayment may increase the attractiveness of a flat rate compared to a measured tariff (i.e., taxi meter effect). Another explanation is provided by Train (1991) who argues that consumers may prefer a flat rate as it is a traditional tariff in the USA and people are accustomed to it (i.e., inertia effect). This effect is closely related to the fact that some consumers may find the tariff evaluation and tariff choice burdensome and thus avoid the

effort of comparing the alternative tariffs. Kling and van der Ploeg (1990) show that in such situations consumers are more likely to choose a flat rate rather than a measured option (i.e., convenience effect). Lastly, in case of some products consumers may choose a flat rate in order to pre-commit themselves to a higher usage (Wertenbroch 1998).

Tariff preferences, however, not always translate into tariff-choice biases. Tariff preferences imply that consumers have an additional willingness to pay for being under their favorite tariff. Consequently, when the preferred tariff is more expensive than an alternative optional tariff, a consumer chooses it anyway, but only when the difference in the bill amount between the optimal tariff and the favorite tariff is lower than this willingness to pay. As a result, a tariff-choice bias is observed. In contrast, when the difference in the bill amount between the optimal tariff and the favorite tariff is larger than the tariff specific willingness to pay, then the consumer chooses the bill-minimizing tariff. In this case the additional bill that would have to be paid under the favorite tariff is not worth the utility that the consumer obtains from this tariff. This discussion suggests that with a low fixed fee a flat rate tariff becomes cheaper and thus consumers with a flat-rate preference and additional willingness to pay are more likely to afford their favorite tariff. Consequently, attractive flat rate would result in high occurrence of flat-rate bias while attractive pay-per-use tariff would result in high occurrence of pay-per-use bias.

Another situation when tariff preferences not necessarily translate into tariff-choice biases is when consumer's preferred and chosen tariff is at the same time his optimal tariff given the usage. Low price of a flat rate implies that flat rate becomes optimal for most usage levels and for most consumers, including those who prefer a flat rate. As a result, a flat-rate bias is difficult to observe because for most consumers who prefer a flat rate, a flat rate is also the optimal tariff. Consequently, the pricing scheme favoring a flat rate may decrease the flat-rate bias occurrence. In such a situation, flat-rate bias will not be observed. Similarly, an attractive pay-per-use tariff will result in lower occurrence of pay-per-use bias.

The discussion above shows that whether a preference translates into a bias depends on the pricing scheme. Therefore, tariff-choice biases are likely to vary with varying pricing schemes. However, two opposite effects exist and the net effect is difficult to predict.

Cost of tariff switching. Another explanation for a tariff-choice bias is the fact that changing a tariff is costly (Mitchell and Vogelsang 1991). Therefore, consumers are not willing to change the tariffs even though they could save money unless the bill difference is substantial.

This is in accordance with the argument that small differences in billing between each alternative tariff justify careless behavior by consumers regarding the choice of an optional tariff (Clay et al. 1992; Srinagesh 1992). This is also consistent with the theory of latitude of price acceptance, arguing that consumers are insensitive to small price differences (Kalyanaram and Little 1994).

Whether a consumer changes the tariff or stays with a suboptimal tariff depends on the bill differences between the existing tariffs given his usage. Since bill difference between the alternative tariffs depends on a pricing scheme, also in this case the pricing scheme has an influence on the tariff-choice bias occurrence.

Cognitive mistakes. Lastly, tariff-choice biases can be also caused by cognitive mistakes made by a consumer. Since consumers choose their tariff based on the expected usage, any incorrect usage prediction may lead to a wrong tariff choice and consequently to a tariff-choice bias (Nunes 2000). Empirical studies provide a support that an overestimation effect leads to a flat-rate bias while an underestimation effect leads to a pay-per-use bias (Lambrecht and Skiera 2006).

However, whether an overestimation or an underestimation effect leads to a bias depends on the break-even point of the pricing scheme. Nunes (2000) proposes that in their tariff choice decision process consumers calculate a break-even point and compare their expected usage with this break-even point. If the expected usage is higher than the break-even point, then consumers choose a flat rate and if the expected usage is lower than the break-even point, then they choose a pay-per-use tariff (Nunes 2000). This decision may be very easy when the break-even point is far away from the expected usage because the consumer can immediately see which tariff is most suitable for him. However, if the break-even point is close to his expected usage, then the choice becomes more difficult which is likely to result in a cognitive mistake and a bias. Consequently, the higher the difference between the break-even point and the expected usage, the lower the tariff-choice bias occurrence.

Table 2. Potential reasons for tariff-choice biases.

| | Reasons of tariff-choice biases | Influence of pricing scheme |
|---|--|--|
| 1 | Tariff preferences (i.e., additional willingness to pay for a favorite tariff) | Influence on tariff attractiveness (i.e., additional payment for a tariff) |
| 2 | Tariff switching cost (i.e., acceptable bill difference) | Influence on the size of the bill difference |
| 3 | Cognitive error (i.e., underestimation and overestimation effect) | Influence on break-even point |

4. Empirical studies

Four empirical studies are conducted to analyze the persistence of tariff-choice biases. The aim of study 1 and study 2 is to analyze the occurrence of tariff-choice biases depending on the varying pricing scheme. In study 1 a tariff-choice bias is identified based on the direct question about the tariff choice and expected usage level similarly to Nunes (2000). A respondent is argued to have a tariff choice bias when he does not choose a bill-minimizing tariff given his expected usage. In study 2 tariff-choice biases are defined based on the consumer surplus rather than on the reported usage level. In this case, for each respondent the consumer surplus is estimated for each tariff and respondents are argued to have a tariff-choice bias when they don't choose a consumer surplus maximizing tariff (Kling and van der Ploeg 1990). In study 3 an analysis of the influence of a marginal price, fixed fee, and break even point on the tariff-choice bias occurrence takes place. Study 4 illustrates the possibilities to skim additional willingness to pay from customers with tariff specific preferences by adjusting the pricing scheme.

4.1. Study 1

4.1.1. Approach

First, the respondents were asked to report their actual monthly Internet usage. The aim of this question was to help subjects to induce their expected usage in the next questions where tariff prices were varied. Next, the respondents reported their Internet usage knowledge on a 5 point Likert scale. In the main task, the respondents were asked to imagine that they were interested in purchasing Internet access. The Internet provider they considered offered two pricing schemes: a flat rate with a fixed fee equal to 40 Euros per month and a pay-per-use tariff with a marginal price equal to 0.50 Euros per hour. The respondents were asked to choose one tariff and estimate the expected Internet usage they would realize similarly to Nunes (2000). In contrast to Nunes (2000), however, the survey design allowed for price and usage interdependence in that respondents were not assumed to have constant, price-independent usage levels but they were allowed to adjust their usage level to the price changes. Next, the respondents were told that their Internet provider introduced some changes in the pricing scheme and they were asked to choose a tariff and estimate expected usage for two additional pricing schemes: (1) flat rate – 20 Euros per month, pay-per-use – 0.70 Euros per hour, (2) flat rate 45 Euros, pay-per-use – 0.30 Euros per hour. The resulting break-even points are: (1) 80 hours, (2) 28.57 hours, and (3) 150 hours. This means that in situation 1 the

consumer using 80 hours would be indifferent towards the tariffs. In case of usage level lower than 80 hours, a pay-per-use tariff would be optimal while in case of usage level higher than 80 hours a flat rate would be optimal. In order to identify the bias the stated usage is compared to the break-even point. Lastly, the subjects were asked about how certain they were about the estimated expected usage.

A survey was conducted on the campus of a major Germany university in May and June 2005. Subjects were randomly selected and asked to voluntarily fill the prepared questionnaire. 171 usable questionnaires were gathered and used for further analysis. The average reported usage equals to 45.17 hours per month which is higher than the average Internet usage in Germany equal to 37.2 hours (ComScore 2006). This is consistent with an expectation that students use more Internet than an average person. Furthermore, 69% of the respondents stated that they know their Internet usage well or very well while as little as 8% reported that they know their usage badly or very badly. Concerning the estimated expected usage under varying tariffs, 57% respondents reported that they are certain or very certain of their expected usage and only 15% stated that they are uncertain or very uncertain.

4.1.2. Results

As already mentioned, two measures for the tariff-choice bias are used in this study. First, the absolute number of respondents with a specific tariff-choice bias (Nunes 2000) and later the tariff-choice bias conditional on the tariff chosen are reported (Lambrecht and Skiera 2006). The results indicate that the occurrence of tariff-choice biases varies with varying pricing schemes which indicates that tariff-choice biases are not persistent across pricing schemes. Table 2 shows that in case of the second pricing scheme that favors a flat rate the occurrence of a flat-rate bias is highest with 14.62% of all respondents choosing a flat rate even though a pay-per-use tariff would be cheaper. Under the first and the third pricing scheme the occurrence of a flat-rate bias decreases to 12.28% and 7.02% of respondents. The differences in tariff-choice bias occurrence are significant ($p < 0.1$). Additionally, a pay-per use bias can be only observed under the second pricing scheme (4.09%). This implies that analyzing consumer behavior only under the first and the third pricing scheme could lead to a wrong conclusion about lack of a pay-per-use bias. In addition to an absolute number of people with a tariff-choice bias, the conditional tariff-choice biases are also reported. In the first case, 38.89% of respondents that chose a flat rate would have saved money choosing a pay-per-use tariff while no one has a pay-per-use bias. In the second case, the percentage of respondents with a flat-rate bias decreases to 22.73% while the percentage of respondents with a pay-per-

use bias increases up to 11.48%. Thus, we can see that conditional tariff-choice biases vary with varying pricing scheme as well.

Table 2. Occurrence of bill based tariff-choice biases for varying pricing scheme.

| | Pricing scheme 1 | Pricing scheme 2 | Pricing scheme 3 |
|---|------------------|------------------|------------------|
| Break-even point in hours | 80 | 28.57 | 150 |
| Fixed fee (flat rate) in Euros | 40 | 20 | 45 |
| Marginal price (pay-per-use tariff) in Euros | 0.50 | 0.70 | 0.30 |
| Absolute tariff-choice bias measure | | | |
| Flat-rate bias in % | 12.28 | 14.62 | 7.02 |
| Pay-per-use bias in % | 0.00 | 4.09 | 0.00 |
| No bias in % | 87.72 | 81.29 | 92.98 |
| Average usage in hours | 68.46 | 73.46 | 63.66 |
| Conditional tariff-choice bias measure | | | |
| Flat-rate bias in % | 38.89 | 22.73 | 37.50 |
| Pay-per-use bias in % | 0.00 | 11.48 | 0.00 |
| # observations | 171 | 171 | 171 |

4.2. Study 2

4.2.1. Approach

In study 2, tariff-choice bias is defined based on consumer surplus rather than reported usage. Similarly to study 1, an Internet access purchase situation is used. First, respondents were presented with a conjoint task where they were asked to rank 16 combinations of monthly Internet consumption in hours and monthly bill as described in Wolk et al. (2007). Based on this conjoint task, individual willingness-to-pay functions for using Internet are estimated for each respondent which are further used to calculate consumer surplus under various tariffs. After the conjoint task respondents were presented with 7 tariff choice situations and they were asked to choose between a flat rate and a pay-per-use tariff similarly to study 1. Table provides prices and resulting break-even points. The tariff-choice bias is identified by comparing the optimal tariff maximizing consumer surplus (see Wolk et al. 2007 for the procedure) with the tariff chosen in the direct question. Additionally, the respondents were asked about how much more expensive a flat rate would have to be before they would switch to a pay-per-use tariff and how much more expensive a pay-per-use tariff would have to be before they would switch to a flat rate.

A survey was conducted on the campus of a major Germany university in May and June 2005. Similarly to study 1, subjects were randomly selected and asked to voluntarily fill the

prepared questionnaire. 300 usable questionnaires were gathered and used for further analysis.

4.2.2. Results

Before analyzing the tariff-choice bias, the results of the conjoint analysis used for willingness-to-pay function estimation are briefly summarized. First, the parameters resulting from the conjoint analysis are highly significant with $p < 0.05$ on average. Only in case of 8 respondents the parameters were not significant at $p = 0.1$. As a result, the analysis proceeds with remaining 292 cases. The average R2 across individuals is equal to 99% with minimum value of 94% and maximum value of 100%. Further, the Kendall Tau correlation coefficient is on average equal to 0.87 with minimum 0.40 and maximum 1.00. These results imply the validity of conjoint analysis task estimation and consequently willingness-to-pay function estimation.

Concerning the tariff-choice biases, the results show that tariff-choice bias occurrence varies across pricing schemes (see Table 3). In case of a fixed fee of 60 Euros and a marginal price of 0.72 Euros only 17.47% of all respondents show a flat-rate bias while in case of a fixed fee of 30 Euros and a marginal price of 0.90 Euros as much as 30.82% of the respondents choose a flat rate even though a pay-per-use tariff would be optimal. Similar results are to be observed with regard to pay-per-use bias. In case of a fixed fee of 60 Euros and a marginal price of 0.72 Euros only 7.88% of respondents show pay-per-use bias, whereas in case of a fixed fee equal to 8 Euros and a marginal price equal to 0.78 Euros as much as 20.55% of the respondents choose a pay-per-use tariff even though a flat rate would maximize consumer surplus. For each tariff choice situation the absolute number of respondents with a flat-rate bias is higher than the number of respondents with a pay-per-use bias.

The analysis of the conditional tariff-choice biases shows similar results in a sense that the percentage of respondents with a tariff-choice biases differs across pricing schemes. Again the occurrence of a flat-rate bias is higher than the occurrence of a pay-per-use bias in most of the cases. Only for the fifth pricing scheme a pay-per-use bias is more prevalent than a flat-rate bias (i.e., 51.23% of all respondents that chose a flat rate would be better off with a pay-per-use tariff, while 52.17% of all respondents that chose a pay-per-use tariff would be better off with a flat rate).

Table 3. Occurrence of consumer surplus based tariff- choice biases for varying pricing scheme.

| | Pricing scheme | | | | | | |
|---|----------------|-------|-------|-------|-------|--------|-------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Break-even point in hours | 66.67 | 33.33 | 70.37 | 83.33 | 10.26 | 118.75 | 22.22 |
| Fixed fee (flat rate) in Euros | 40 | 30 | 38 | 60 | 8 | 57 | 16 |
| Marginal price (pay-per-use tariff) in Euros | 0.60 | 0.90 | 0.54 | 0.72 | 0.78 | 0.48 | 0.72 |
| <i>Absolute tariff-choice bias measure</i> | | | | | | | |
| Flat-rate bias in % | 30.14 | 30.82 | 23.29 | 17.47 | 28.42 | 21.92 | 28.42 |
| Pay-per-use bias in % | 19.18 | 10.27 | 18.15 | 7.88 | 20.55 | 18.15 | 18.84 |
| No bias in % | 50.68 | 58.90 | 58.56 | 74.66 | 51.03 | 59.93 | 52.74 |
| <i>Conditional tariff-choice bias measure</i> | | | | | | | |
| Flat-rate bias in % | 77.88 | 71.43 | 61.26 | 83.61 | 51.23 | 65.98 | 54.24 |
| Pay-per-use bias in % | 44.80 | 25.00 | 38.13 | 21.90 | 52.17 | 38.97 | 47.83 |
| # observations | 292 | 292 | 292 | 292 | 292 | 292 | 292 |

One question emerges when analyzing Table 3. One can clearly see that the overall bias occurrence is rather persistent and oscillates between 20-30% in case of a flat-rate bias and between 10-20% in case of a pay-per-use bias. However, we don't know whether the bias occurs for the same or for different respondents. This question is addressed by inspecting the average occurrence of tariff-choice biases per individual across 7 different tariff choice situations. The results are reported in Table 4 and they show that only 19.86% and 9.25% of respondents have a flat rate and a pay-per-use bias respectively in at least 3 tariff choice situations. Further, only 0.34% of all respondents in case of a flat-rate bias and 1.37% of all respondents in case of a pay-per-use bias have a tariff-choice bias consistently across 7 pricing schemes. These results show that although the overall number of respondents with tariff-choice biases stays constant, these are not the same respondents. Instead, respondents with a tariff-choice bias switch to an optimal tariff or the change in a pricing scheme justifies their tariff choice. On the other hand, respondents having an optimal tariff start having a tariff-choice bias. Therefore, while the overall persistence is rather high, the individual persistence can be considered as rather low.

Table 4. Individual persistence of tariff- choice biases.

| Bias occurrence | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|------------------|-------|-------|-------|-------|-------|------|------|------|
| Flat-rate bias | 27.74 | 20.21 | 16.44 | 19.86 | 13.01 | 1.03 | 1.37 | 0.34 |
| Pay-per-use bias | 52.40 | 15.07 | 15.41 | 9.25 | 3.77 | 1.71 | 1.03 | 1.37 |

Additionally, the respondents were asked directly how much higher the bill under a flat rate would have to be before they would switch to a pay-per-use tariff and vice versa. The results show a very interesting pattern. First of all, only a minority of the respondents would switch to a cheaper tariff, while a majority would accept having a more expensive tariff. Interestingly, while 94% respondents accept staying with a flat rate even though a pay-per-use tariff would be less expensive only 87% accept staying with a pay-per-use tariff even though a flat rate would be less expensive. Respondents would, however, stay under a more expensive tariff only until the bill difference between the tariffs does not surpass 9.80 Euros in case of a pay-per-use tariff and 12.40 Euros in case of a flat rate. These results suggest that the consumers perceive tariff switching as costly and they are willing to stay under a more expensive tariff until the cost difference does not surpass the threshold. Further analysis shows that 48% of respondents are willing to pay for a flat rate as much as for a pay-per-use tariff – 9.34 Euros, 37% is willing to pay on average 20.25 Euros more for a flat rate than for a pay-per-use tariff while 12% is willing to pay on average 8.91 Euros more for a pay-per-use tariff than for a flat rate. These results are in line with previous literature. Lambrecht and Skiera (2006) report that flat-rate bias amount is equal to 100% more than bill of the cheapest tariff, while pay-per-use amount is equal to 20% more than the bill of the cheapest tariff. Further, Kridel et al. (1993) show the amount of flat-rate bias equal to \$9.49 monthly, while Della Vigna and Malmendier (2006) report \$22 monthly which results in \$700 during the whole membership period. Lastly, Nunes (2000) reports an average flat-rate bias amount of \$230 per year which gives \$19.17 per month.

4.3. Study 3

Study 1 and study 2 show that tariff-choice bias occurrence varies across pricing schemes with regard to two tariff-choice bias definitions. Study 3 analyses in more detail the effect of varying pricing schemes and the effect of differences between break-even point and expected usage on tariff-choice bias occurrence. Consequently, more manipulations of pricing scheme and reported expected usage are included in this study.

4.3.1. Approach

Similarly to previous studies, Internet access was analyzed. After reporting their average Internet usage, respondents were confronted with 13 tariff choice situations where the prices as well as break-even point were varied. A price of a flat rate ranged between 16 and 55 Euros, a marginal price ranged between 0.43 and 2.20 Euros, and break-even point ranged

between 10 and 83 hours. After choosing a tariff, respondents were asked to estimate their expected usage similarly to study 1. Lastly, subjects reported their certainty with regard to the estimated expected usage.

An online survey was conducted at major German university. The link to a survey was sent to all students of Faculty of Business and Economics. The link was active in the period May – July 2006. 207 subjects voluntarily completed the survey. The average reported usage equals to 62.35 with a median of 40 hours. While the average Internet usage in Germany is equal to 37.2 hours (ComScore 2006), students are expected to use more than an average person. Additionally, 78% of the respondents stated that they were certain or very certain of the estimated expected usage while only 2% stated that they were uncertain or very uncertain.

4.3.2. Results

In order to analyze the effect of prices and break-even point on the probability of the tariff-choice bias occurrence the following multinomial logit model is estimated:

$$P_{ip}(B = k) = \frac{\exp(U_{ip})}{\sum \exp(U_{ip})}$$

$$U_{it} = \beta_{0j} + \beta_{1j}F_t + \beta_{2j}p_t + \beta_{3j}BED_{it} + e_{it}$$

where k is equal to 1 in case of a flat-rate bias, 2 in case of a pay-per-use bias, and 3 in case of no bias, F_t is a fixed fee at the choice situation t, p_t is a marginal price at the choice situation t, and BED_{it} is the difference between the break-even point and the expected usage for each individual i in the tariff choice situation t. The results are reported in Table 5. The estimated model is highly significant with Nagelkerke's R2 equal to 22% and correct classifications equal to 86% which is higher than proportional chance criterion. The results show that a fixed fee and a marginal price have a significant effect on a flat-rate bias occurrence. First, a fixed fee significantly decreases the probability of having a flat-rate bias ($\beta_{11} = -0.01$, $p < 0.1$). This means that when a flat rate becomes more expensive, the respondents are less likely to end up having a flat-rate bias. Additionally, the results show that a higher marginal price leads to a lower probability of having a pay-per-use bias. Similarly to a flat-rate bias this means that when a pay-per-use tariff becomes more expensive then respondents are less likely to choose it and end up having a pay-per-use bias. The effect is, however, not significant. Furthermore, the higher the marginal price, the lower the

probability of flat-rate bias occurrence ($\beta_{21} = -1.88$, $p < 0.01$). To sum up, the results show that increasing prices lead to a decreasing probability of observing tariff-choice biases.

With regard to the difference between break-even point and the expected usage, the results show a highly significant effect on the probability of flat-rate ($\beta_{31} = -0.04$, $p < 0.01$) and pay-per-use bias occurrence ($\beta_{32} = -0.10$, $p < 0.01$). Consequently, the more the break-even point deviates from the expected usage the smaller the probability of having a tariff-choice bias. Higher differences between expected usage and break-even point imply higher differences in the bill amount between a flat rate and a pay-per-use tariff. Therefore, from the results it can be also concluded that the higher the difference in bill amount between tariffs, the lower the probability of having a tariff-choice bias. This supports the notion that consumers do not choose their favorite tariff when the bill difference is too big.

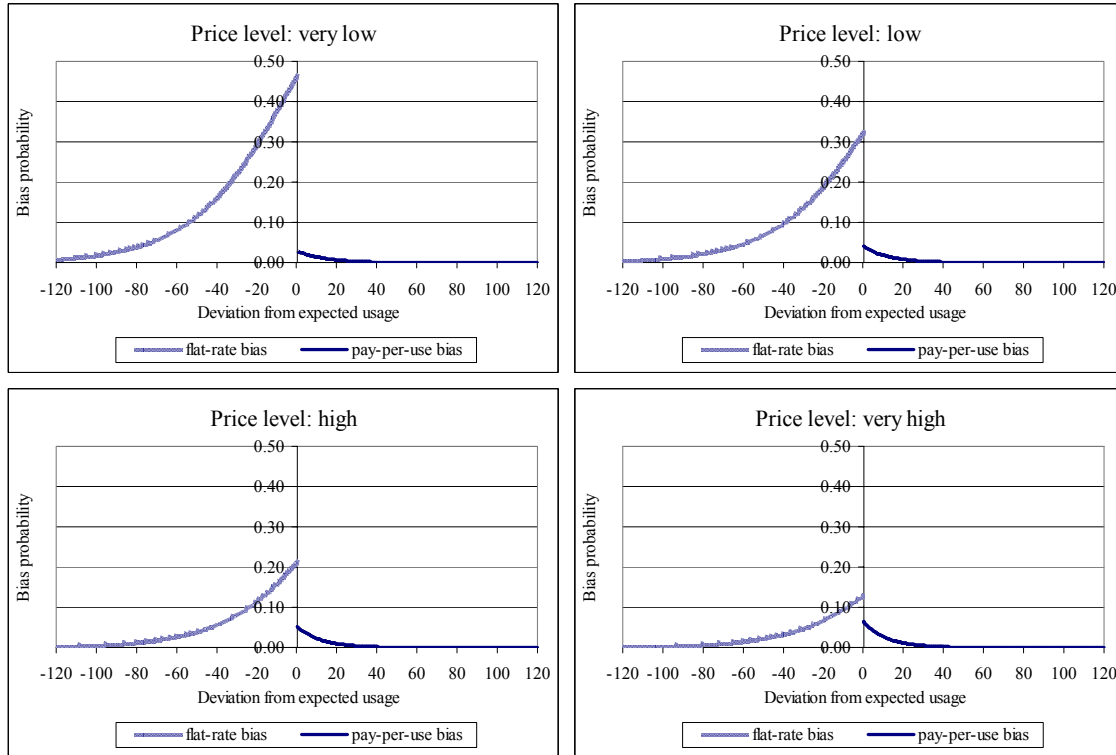
Table 5. Influence of pricing characteristics on tariff-choice bias probability.

| Variable | Parameters | |
|---|-----------------|------------------|
| | Flat-rate bias | Pay-per-use bias |
| Intercept | 1.06 (0.22)*** | -3.09 (0.89)*** |
| Fixed fee | -0.01 (0.01)* | 0.01 (0.02) |
| Marginal price | -1.88 (0.20)*** | -0.03 (0.43) |
| Difference between BEP and expected usage | -0.04 (0.00)*** | -0.10 (0.02)*** |
| Log-likelihood | -463.63 | |
| Model Significance | 0.00 | |
| Nagelkerke R2 | 0.22 | |
| Proportional Chance Criterion | 0.77 | |
| Correct Classifications | 0.86 | |

* Significant at $p = 0.10$, ** Significant at $p = 0.05$, *** Significant at $p = 0.01$. Standard deviations appear in parentheses.

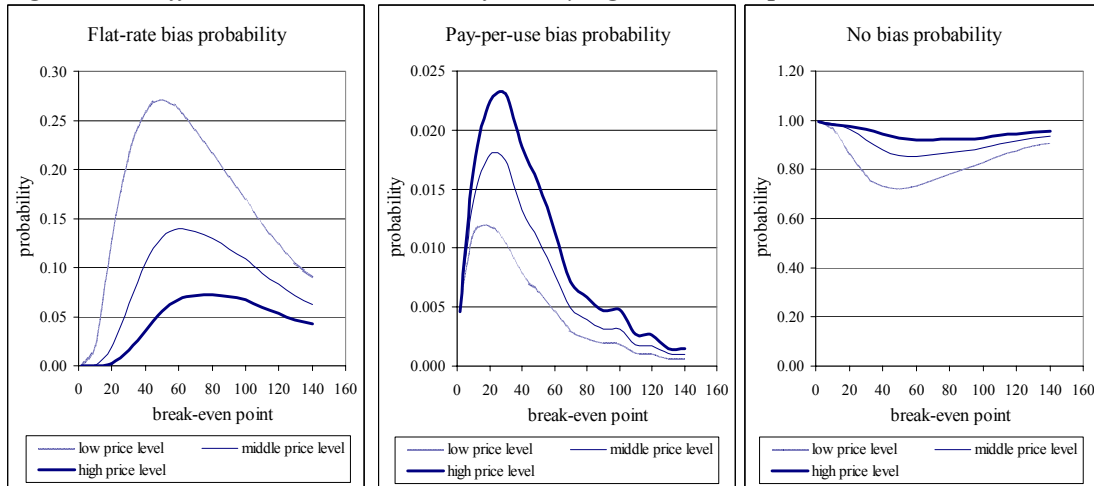
Based on the estimated model, the occurrence of tariff-choice biases is simulated for various levels of differences between the break-even point and expected usage as well as for different price levels (see Figure 1). Keeping break-even point equal to 40 hours, the expected usage is varied. Four price levels are used: (1) very low, (2) low, (3) high, (4) very high which always resulted in break-even point equal to 40. The results show that both flat rate and pay-per-use bias occurrence is highest when the break-even point is equal to expected usage. The more the expected usage deviates from the break-even point, the lower the probability of observing a tariff-choice bias. For each price level a higher occurrence of flat-rate bias is observed. Lastly, Figure 1 shows that occurrence of flat-rate bias decreases with an increasing price level.

Figure 1. Tariff choice bias occurrence for various price levels.



In the last step, the model is used to analyze the tariff-choice bias occurrence with relation to the break-even point. The probability of tariff-choice bias occurrence is estimated for each individual in a sample. Three price levels are chosen: (1) low (fixed fee equal to 20), (2) middle (fixed fee equal to 40), (3) high (fixed fee equal to 60). The break-even point is varied by changing a marginal price. A simulation where a marginal price is kept constant and a fixed fee is varied leads to consistent effects. Figure 2 shows the highest tariff choice bias occurrence for break-even point in the range of 30 - 60. The average usage in the sample is equal to 62.35 and median to 40 hours. Consequently, we see the highest tariff-choice bias occurrence for break-even point close to expected usage.

Figure 2. Tariff-choice bias occurrence for varying break-even point.



4.4. Study 4

4.4.1. Approach

The aim of study 4 is to validate the findings from study 3 and show how an appropriate pricing scheme can help to skim additional tariff-specific willingness to pay. Consequently, in study 4 the relationship between tariff preferences and tariff-choice bias occurrence is investigated under two pricing schemes. Similarly to previous studies, respondents were confronted with a hypothetical Internet access purchase situation. First, respondents were asked about their general tariff preferences similarly to Prelec and Loewenstein (1998). Next, they were presented with two tariff choice situations and were asked to pick one tariff: (1) flat rate – 38 Euros per month or pay-per-use – 0.60 Euros per hour resulting in a break-even point of 63.33 hours in case of the first tariff choice and (2) flat rate – 30 Euros per month or pay-per-use – 0.72 Euros per hour resulting in a break-even point of 41.67 hours in case of the second tariff choice. Tariff choice decision was followed by a question related to the estimated expected usage level.

210 subjects from the Rhein-Main area in Germany were approached in the period of January und February 2006 and asked to voluntarily fill a questionnaire. 176 usable questionnaires including 87 women and 89 men were obtained and used for a further analysis. Most of the respondents were between 20 – 29 years old (52.3%) and between 30 – 39 years old (30.7%). Average expected usage in tariff choice situation 1 is equal to 43.81 hours while in situation 2 – 44.74 hours. From that it can be seen that under pricing scheme 1 the difference between the break-even point and expected usage is higher than under pricing scheme 2 (19.52 and 3.07 respectively).

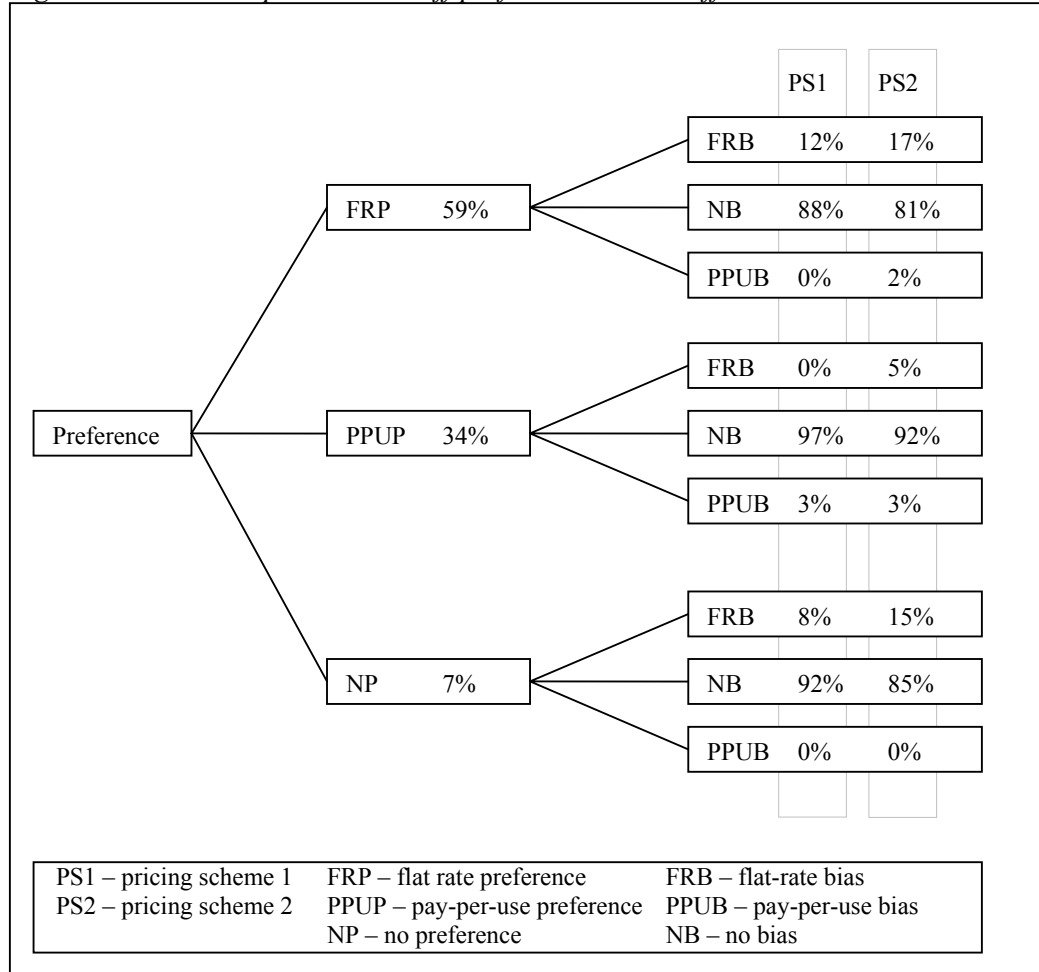
4.4.2. Results

Similarly to study 1, the tariff-choice bias is identified by comparing the reported tariff choice and usage level with the break-even point. Figure reports the results. First, the results show that 59% of respondents have a preference for a flat rate while 34% of respondents have a preference for a pay-per-use tariff. Only 7% of respondents declared no tariff preferences. Compared to results of Prelec and Loewenstein (1998) who report that on average 48% of respondents have a preference for a flat rate, 28% of respondents have a preference for a measured option, and 20% don't have any tariff specific preferences, the results of this study indicate slightly higher level of tariff preferences.

Study 3 showed that varying pricing scheme influences tariff-choice bias occurrence in such a way that for small differences between the break-even point and the average expected usage the tariff-choice bias occurrence is high while for high differences the tariff-choice bias occurrence is low. Figure 3 shows to what extent tariff preferences translate into tariff-choice biases depending on the pricing scheme. Under pricing scheme 1 among respondents with a flat rate preference only 12% have a flat-rate bias. Consequently, as much as 88% of respondents having a flat rate preference don't have tariff-choice bias. These results imply that many consumers may be potentially willing to pay additionally for a flat rate; however, the company loses this potential profit as the pricing scheme is not adequately designed. Similar results are observed with regard to a pay-per-use preference. Majority of the respondents with a pay-per-use preference has no tariff bias (97%). For most of them a bias can not be observed because their preferred tariff is at the same time the optimal tariff given the usage and pricing scheme.

In case of pricing scheme 2, the difference between the resulting break-even point and average usage is smaller than in case of scheme 1. Figure 3 shows that flat-rate bias occurrence increases for consumers with flat rate preference from 12% to 17%. Additionally, an increase in other groups can be observed which is driven mostly by the cognitive errors. This implies that break-even point influences the tariff-choice bias occurrence no matter whether it is caused by preferences, switching costs or cognitive errors.

Figure 3. Relationship between tariff preferences and tariff-choice biases.



5. Conclusions

The occurrence of tariff-choice biases is well documented in various empirical studies. Nevertheless, no study so far has analyzed how persistent tariff-choice biases are across varying pricing schemes and how consumers react when their preferred tariff becomes too expensive. This study shows that pricing scheme has a significant effect on the occurrence of tariff-choice biases. With a usage of two different definitions of tariff-choice biases (1) based on the usage level and break-even point and (2) based on the consumer surplus and with a usage of two different measures: (1) absolute and (2) conditional tariff bias measure, the results show that the number of respondents with tariff-choice biases varies with varying pricing schemes. Specifically, flat rate bias occurrence is shown to vary between 7% and 15% in study 1 and between 17% and 31% in study 2 while pay-per-use bias vary between 0% and 4% in study 1 and between 8% and 20% in study 2. More detailed analysis shows that an increase in prices leads to a decrease in tariff choice bias occurrence. Consequently, when

tariff prices are low consumers who have a tariff specific preference can afford to buy their favorite tariff. In contrast, high prices lead to decrease in tariff-choice bias occurrence.

Furthermore, the empirical analysis shows that high deviations of break-even point from average expected usage lead to small tariff-choice bias occurrence, while small deviations increase tariff-choice bias occurrence. The reason is that small deviations between break-even point and average usage mean small differences in the bill amount between optional tariffs which implies that: (1) favorite tariffs are more affordable, (2) bill difference is likely to be lower than tariff switching costs, (3) cognitive mistakes are more likely to be made. As a result of these three effects a higher tariff-choice bias occurrence is observed for small deviations of break-even point from average expected usage.

These results have important managerial implications. They suggest that a company providing a set of optional tariffs can influence the occurrence of tariff-choice biases and consequently its profits. As shown in Lambrecht and Skiera (2006) tariff-choice biases translate into profit such that flat-rate bias can lead to a profit increase, while a pay-per-use bias increases consumers churn rate. Results of this study show that 59% of consumers have a flat-rate preference and average willingness to pay for a flat rate equal to 20.25 Euros. Under a pricing scheme with high deviations between average expected usage and break-even point, a company can skim this additional willingness to pay for a flat rate only in case of a small subset of consumers. In contrast, a pricing scheme with break-even point close to the average expected usage allows skimming more additional willingness to pay. Therefore, tariff-choice biases should be considered when designing a nonlinear pricing scheme. Additionally, the results support the usage of multiple optional tariffs resulting in multiple break-even points. However, future research should further analyze the influence of number of tariffs in the pricing scheme on the tariff-choice bias occurrence.

Limitations

The aim of the study motivated the usage of survey data. As a result, a lower level of realism compared to an analysis based on transactional data should be kept in mind. Another limitation is that the analysis does not account for demand uncertainty. Lambrecht et al. (2007) show that demand uncertainty influences tariff choice and may thus also influence the probability of tariff-choice bias. Nevertheless, demand uncertainty is not expected to change the results of this study. Additionally, the empirical study does not account for usage

variation across time. Since the focus of this study was tariff choice persistence across pricing schemes rather than across time, future research might investigate both aspects.

References

- Ben-Akiva, M., Bradley, M. D., Morikawa, T., Benjamin, J., Novak, T. P., Oppewal, H., & Rao, V. (1994). Combining Revealed and Stated Preferences Data. *Marketing Letters*, 5(4), 335-350.
- Clay, K., Sibley, D. S., & Srinagesh, P. (1992). Ex Post vs Ex Ante Pricing: Optional Calling Plans and Tapered Tariff. *Journal of Regulatory Economics*, 4(2), 115-138.
- Comscore. (2006). 694 Million People Currently Use the Internet Worldwide According To comScore Networks. Press Release, URL: <http://www.comscore.com/press/release.asp?press=849>, retrieved on 29.06.2006.
- DellaVigna, S., & Malmendier, U. (2006). Paying Not To Go To The Gym. *American Economic Review*, 96(3), 694-719.
- Essegaier, S., Gupta, S., & Zhang, Z. J. (2002). Pricing Access Services. *Marketing Science*, 21(2), 139-159.
- Hobson, M., & Spady, R. H. (1988). The Demand for Local Telephone Service under Optional Local Measured Service. *Bellcore Economics Discussion Paper No 50*.
- Iyengar, R. (2005). A Structural Demand Analysis for Wireless Services under Nonlinear Pricing Schemes. Working Paper, Columbia University.
- Kalyanaram, G., & Little, J. D. C. (1994). An Empirical Analysis of Latitude of Price Acceptance in Consumer Package Goods. *Journal of Consumer Research*, 21(3), 408-418.
- Kling, J. P., & Ploeg, S. S. v. d. (1990). Estimating Local Elasticities with a Model of Stochastic Class of Service and Usage Choice. In A. d. Fontenay & M. H. Shugard & D. S. Sibley (Eds.), *Telecommunications Demand Modelling. An Integrated View*. Amsterdam: North Holland.
- Kridel, D. J., Lehman, D. E., & Weisman, D. L. (1993). Option Value, Telecommunication Demand, and Policy. *Information Economics and Policy*, 5(2), 125-144.
- Lambrecht, A., Seim, K., & Skiera, B. (2007). Does Uncertainty Matter? Consumer Behavior under Three-Part Tariffs. *Marketing Science*, forthcoming.
- Lambrecht, A., & Skiera, B. (2006). Paying Too Much and Being Happy About It: Causes and Consequences of Tariff-Choice Biases. *Journal of Marketing Research*, 43(2), 212-223.
- Miravete, E. (2002). Choosing the Wrong Calling Plan? Ignorance and Learning. *American Economic Review*, 93(1), 297 – 310.

- Mitchell, B. M., & Vogelsang, I. (1991). *Telecommunication Pricing: Theory and Practice*. Cambridge, UK: Cambridge University Press.
- Nunes, J. (2000). A Cognitive Model of People's Usage Estimations. *Journal of Marketing Research*, 37(November), 397-409.
- Nunes, J. C. (1999). Buying What You Will Use, Or Using What You Buy: Do Consumers Optimize Purchase Quantities. Working Paper, University of Southern California.
- Prelec, D., & Loewenstein, G. (1998). The Red and the Black: Mental Accounting of Savings and Debt. *Marketing Science*, 17(1), 4-28.
- Schulze, T., & Gedenk, K. (2005). Biases bei der Tarifwahl und ihre Konsequenzen für die Preisgestaltung. *Zeitschrift für Betriebswirtschaft*, 75, 157-184.
- Skiera, B. (1999). *Mengenbezogene Preisdifferenzierung bei Dienstleistungen*. Wiesbaden.
- Srinagesh, P. (1992). A Dynamic Stochastic Model of Choice. *Bellcore Economics Discussion Paper No 78*.
- Tacke, G. (1989). *Nichtlineare Preisbildung: Höhere Gewinne durch Differenzierung*. Wiesbaden.
- Train, K. E. (1991). *Optimal Regulation. The Economic Theory of Natural Monopoly*. Cambridge (Mass.): MIT Press.
- Train, K. E., McFadden, D. L., & Ben-Akiva, M. (1987). The Demand for the Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *Rand Journal of Economics*, 18(1), 109-123.
- Wertenbroch, K. (1998). Consumption Self-Control via Purchase Quantity Rationing. *Marketing Science*, 18(4), 317-337.
- Wertenbroch, K., & Skiera, B. (2002). Measuring Consumers' Willingness to Pay at the Point of Purchase. *Journal of Marketing Research*, 39(2), 228-241.
- Wolk, A., Skiera, B., & Schlereth, C. (2007). Augmented Methods of Conjoint Analysis to Estimate Willingness to Pay for Multiple-Unit Products. Working Paper, University of Frankfurt.

The Effects of Reference Prices on Bidding Behavior in Interactive Pricing Mechanisms

Agnieszka Wolk

Martin Spann

Wolk, A. and Spann, M. (2007). The Effects of Reference Prices on Bidding Behavior in Interactive Pricing Mechanisms, under review at Journal of Interactive Marketing.

The Effects of Reference Prices on Bidding Behavior in Interactive Pricing Mechanisms

Abstract

Reference prices have a significant effect on consumer behavior in the posted-price scenario. Consumers compare them to the actual price of the product and any perceived gain or loss influences their purchase decision. Their role, however, changes in the increasingly popular interactive pricing mechanisms used in online retailing, e.g., auctions and name-your-own-price. In this context, a reference price is no longer used to judge the actual posted price but to determine a consumer's bid for the product. In this study, we analyze the effects of reference prices on consumers' bidding behavior. We find significant influence of different reference price concepts on bid values, which shows that with regard to product valuation the effects of reference prices are robust across various purchase scenarios. In contrast, with regard to search behavior and purchase intentions we extend previous results and show how the role of reference prices changes in interactive pricing scenarios.

Keywords: reference price, online auction, bidding behavior.

1. Introduction

The Internet has led to the emergence of a set of interactive pricing mechanisms, such as eBay auctions (e.g., eBay.com) or name-your-own-price auctions (e.g., priceline.com, expedia.com, germanwings.com), which are constantly gaining popularity among consumers and retailers (Bapna 2005). The distinctive characteristic of these mechanisms is that they give consumers more control over the pricing process and the final price to pay (Chandran and Morwitz 2005). In doing so, these mechanisms require consumers to determine the value of their bid for the product, which is quite different from their either accepting or rejecting a seller's price in the traditional, posted-price scenario (Spann and Tellis 2006). This flexibility is, however, related to considerable uncertainty about the product value (Chernev 2003), which consequently increases the effect of various forms of price information on consumer behavior. The focus of this study is on one specific interactive pricing mechanism – the so called “name-your-own-price” auction (NYOP) – where the seller specifies a hidden minimum threshold price that has to be met by the bidder for the purchase to be executed (Spann et al. 2004).

One of the most relevant pieces of information in interactive pricing mechanisms that could influence bidding behavior is the information about a reference price (Chernev 2003; Kamins et al. 2004). Various reference price concepts have been proposed in the literature: (a) an internal reference price (IRP), which consumers retain in their memories, based on their experience (Mayhew and Winer 1992); (b) an external reference price (ERP) formed at the point of purchase based on various cues such as current prices for other products in the same category (Briesch et al. 1997; Mazumdar and Papatla 1995; Mazumdar and Papatla 2000; Kumar et al. 1998; Rajendran and Tellis 1994), a current price for a product bought on previous purchase occasions (Hardie et al. 1993), or prices in competing stores (Della Bitta et al. 1981); and lastly a specific type of an external reference price, (c) an advertised reference price (ARP) in the form of a seller-provided regular price or suggested retail price presented often in price advertisements (Compeau and Grewal 1998; Grewal et al. 1998; Jensen et al. 2003; Urbany et al. 1988). A main feature of an ARP is that it is determined by the seller at his desired level and may therefore lack the credibility of an ERP.

A significant effect exerted by reference prices on consumer behavior has been found in the posted-price scenario common in traditional retailing (Kalyanaram and Winer 1995). Empirical studies show that consumers compare their reference price to the actual price of the

product and that any perceived gain or loss influences their purchase decision (Della Bitta et al. 1981; Monroe 1977).

This well-documented effect in the posted-price scenario is not, however, entirely applicable in the case of interactive pricing mechanisms, where the actual price is a result of the bidding process. Since no actual price is available prior to their submitting a bid, consumers can no longer compare their reference price to the actual price of the product. Instead, the reference price plays an even more important role in the situation of product value uncertainty, as it can influence whether the consumer takes part in the auction and it can determine the bid value. Since in NYOP consumers determine their bid value based on their product valuation (Spann et al. 2004), a reference price plays a key role, because it is an important benchmark for product value estimation (Chernev 2003). In addition, a reference price can signal the value that the seller places on the product (Kamins et al. 2004), which may also influence the bid value. As a result, consumers' purchase decision, bid values and company profits may depend to a large extent on the price information that consumers encounter prior to submitting their bids. This, consequently, has important implications for name-your-own-price retailers, as the inclusion of appropriate information on their websites may increase their profits.

Although existing studies have broadly researched the role of a reference price in the offline posted-price scenario, the interactive pricing mechanisms applicable in the online environment have been rather neglected. The first step in this direction has been done by Jensen et al. (2003), who investigate the influence of a reference price in online retailing and conclude that the effect of a reference price is different in online and offline environments. The authors, however, analyze a posted-price scenario which differs from the situation when consumers can determine the actual price through the bidding process. In the context of interactive pricing mechanisms, Chernev (2003) analyzes the effect of an internal and an external reference price on the ease of bidding and the perceived likelihood of success in the name-your-own-price auction. However, the study omits effects on the bid value and purchase intentions. Kamins et al. (2004) investigate the effect of seller-supplied reference prices in the form of the minimum bid and the reservation bid, while Dholakia and Simonson (2005) analyze the effect of external reference prices in the form of prices fetched in adjacent auctions in the context of eBay auctions. Although the latter studies investigate the effect of a reference price on the bid value, they focus only on one reference price concept at a time and do not account for interaction effects between them. Additionally, the results of Kamins et al. (2004) and Dholakia and Simonson (2005) are not entirely applicable in the context of a

name-your-own-price auction where value uncertainty is higher due to the absence of external price cues in the form of other people's bids. Moreover, no distinction is made between plausible and exaggerated reference prices, even though an analysis of this effect is of considerable interest (Jensen et al. 2003; Kamins et al. 2004) and of high importance to managers. Lastly, consumer search behavior is neglected.

Consequently, the aim of this paper is to analyze the effect of a reference price on bidding behavior in one specific interactive pricing mechanism, the name-your-own-price auction, with respect to the bid value, search behavior, and purchase intentions. In contrast to previous studies, we distinguish between three reference price concepts, namely an internal, an external and an advertised reference price, and we determine their effect on bid values. We also distinguish between both plausible and exaggerated values of the ARP as suggested by Jensen et al. (2003) and Kamins et al. (2004).

Our work contributes both to the interactive pricing literature and to the reference price literature. First of all, we analyze the effect exerted by a reference price on consumers' bid values, purchase intentions and search behavior in an interactive pricing scenario. Second, to the best of our knowledge this is the first study that analyzes the effect of three different reference price concepts, namely an internal, an external, and an advertised reference price. Previous studies encompass only an internal and an external reference price (e.g., Mayhew and Winer 1992; Rajendran and Tellis 1994). Third, we specifically focus on the name-your-own-price auction where, to the best of our knowledge, the effect of a reference price on the bid value has not yet been analyzed. In addition, we show whether the retailer can use an ARP to increase its profits in name-your-own-price auctions.

The remainder of the paper is organized as follows. First, we develop hypotheses on how various reference price concepts influence bidding behavior in name-your-own-price auctions. Next, we present the design of an empirical study to test these hypotheses and report the results. Finally, we discuss our results and provide implications.

2. Conceptual model

A reference price is defined as a norm that serves as a neutral point for judging the actual prices (Kalyanaram and Winer 1995). Various theories have been proposed to explain the effect of a reference price on consumers behavior, most prominently: (1) the adaptation-level theory, i.e., consumers form an "adaptation level" through exposure to past stimuli and response to a current stimulus based on that level (Helson 1964) and (2) the assimilation-

contrast theory, i.e., a new stimulus encountered by an individual is judged against a reference point that is formed on the basis of past experience; new stimuli that are close to an adaptation level are assimilated and perceived to be closer than they actually are, while stimuli that diverge sharply from that level provide the contrast effect (Sherif 1963).

The effect of a reference price has been extensively analyzed in the posted-price scenario where consumers face a posted price charged for the product and make a decision as to whether they accept this price and conduct a purchase or not (Kalwani et al. 1990; Rajendran and Tellis 1994; Winer 1986). The results show that consumers use reference prices to judge the current actual price of the product. Prices below the reference price are perceived to be low (relatively inexpensive) and thus regarded as gains, while prices above it are perceived to be high (relatively expensive) and thus regarded as losses (Kalyanaram and Winer 1995).

This mental mechanism, however, does not apply in case of name-your-own-price auctions where it is the consumer who sets the price of the product by submitting her bid. Specifically, in name-your-own-price auctions the seller specifies a hidden minimum threshold price that has to be met if the purchase is to be executed. Consequently, the bid submitted by the buyer is accepted or rejected depending on whether it exceeds this hidden threshold price. As a result, the use of reference prices is different in name-your-own-price auctions. The consumer no longer compares the reference price to the actual price of the product, as there is no actual price given. Instead, the reference price indicates the value of the product (Chernev 2003) and influences the bid value submitted by the consumer (Spann et al. 2004). Below, we derive hypotheses for the effects of the three reference price concepts existing in the literature on the bid value: an internal reference price, an external reference price, and an advertised reference price.

An internal reference price is the price that a consumer has in her memory and that is formed on the basis of past experience. The effect of an internal reference price on the bid value can be derived from Thaler (1985), who postulates that the total value of the product consists of two components: (1) acquisition utility, which is a measure of the value of the product purchased relative to its price and (2) transaction utility, defined as the difference between the price paid and the internal reference price for the product (Thaler 1985). According to Thaler's theory, the overall perceived value of a product that a consumer is considering purchasing can be affected by that consumer's internal reference price. Further studies provide support for this notion. Ranyard et al. (2001) find that an internal reference price

influences the product valuation. Consequently, we propose that an internal reference price will have a positive effect on the bid value.

H1. An internal reference price (IRP) will have a positive effect on the bid value.

Often, however, consumers may be uncertain about their IRP or may not have an IRP at all (Dickson and Sawyer 1990). In this case, they lack a benchmark for their bid determination process (Chernev 2003). Consequently, consumers are likely to search for an external reference price that can help to relieve their uncertainty about the product's value. Empirical studies indicate a significant effect of an ERP on consumer behavior both in the posted-price scenario (Hardie et al. 1993; Kumar et al. 1998; Mazumdar and Papatla 1995; Rajendran and Tellis 1994) as well as in the context of eBay auctions (Dholakia and Simonson 2005). Consumers, however, react not to absolute prices, but to relative prices (Krishnamurthi et al. 1992). Thus, an ERP will have a positive effect on the product value estimation only when it is higher than the initial IRP. Otherwise, the product value estimation is likely to decrease. Consequently, this influences the bid value.

H2. An external reference price (ERP) will have a positive effect on the bid value if it is higher than the initial IRP and a negative effect if it is lower than the initial IRP.

In order to diminish value uncertainty and increase the submitted bids, the retailer may provide a suggested regular price on his website, i.e., an advertised reference price. This strategy is beneficial as the buyer's valuation of the product may not be constant but change as she obtains more information about the price range prevailing in the market (Monroe 2003). Thaler (1985) postulates that a high advertised reference price compared to a low selling price provides a positive transaction utility and thus increases the estimated product value (Thaler 1985). Support for this notion and a significant effect of seller-supplied reference prices has been provided both in the posted-price scenario (e.g., Urbany et al. 1988) as well as in the context of online auctions (Kamins et al. 2004). Again, however, consumers do not perceive prices in terms of absolute values, but instead compare them to their IRP. Biswas and Blair (1991) argue that the effect of an ARP will be positive when it exceeds an IRP and negative when it is lower than an IRP.

H3. An advertised reference price (ARP) will have a positive effect on the bid value if it is higher than the initial IRP and a negative effect if it is lower than the initial IRP.

When providing an ARP, the retailer has a wide choice of different values, both plausible and implausible ones. A plausible reference price may decrease the product valuation among

some buyers, depending on whether an ARP is higher or lower than their initial belief (Biswas and Blair 1991). An exaggeratedly high ARP, that is more likely to be higher than an IRP, can thus increase the product valuation and the bid value. Nevertheless, the assimilation-contrast theory suggests that if an ARP is too high, consumers are likely to reject it and it might thus not have any effect at all on the bid value. Contrary to this theory, empirical studies show that an exaggerated ARP, even though often discounted by consumers, may still increase their perceptions of the product value (e.g., Compeau and Grewal 1998; Monroe 2003; Urbany et al. 1988) sometimes even more than a plausibly high reference price (Biswas 1992; Biswas and Blair 1991; Burton et al. 1993; Lichtenstein et al. 1991). Therefore, we argue that an exaggerated ARP will have a stronger positive influence on the bid value than a plausible ARP.

H4. An exaggerated ARP will have a stronger (positive) influence on the bid value than a plausible ARP.

By providing an ARP retailers may influence consumer search behavior, which is likely to have a strong impact on name-your-own-price retailers. The low cost of doing business on the Internet, the great number of competitors and the ease of making price comparisons all tend to drive prices down on the Internet (Zettelmeyer 2000). Thus, consumers who conduct search are likely to find rather low prices, leading to a lower bid. Consequently, the retailer may want to deter consumers from conducting external search. By providing an ARP on its website, the seller can decrease value uncertainty and thus decrease the need to undertake external search (Urbany 1986). Previous research in the posted-price scenario shows that when buyers are exposed to an ARP, their willingness to conduct additional search decreases, as the perceived benefits of search are lower than the costs of search (Della Bitta et al. 1981; Urbany et al. 1988). Since propensity to undertake search online has been shown to be similar to propensity to undertake search offline (Jensen et al. 2003), we propose that the presence of an ARP will decrease the magnitude of external price search.

H5. The magnitude of price search will be lower in the presence of an advertised reference price (ARP).

So far, we discussed potential advantages of including an ARP on the retailer's website. However, the online environment enables consumers to conduct easy and fast search as well as provides access to an abundance of detailed product information (Zettelmeyer 2000). Therefore, many consumers may still conduct some external search in spite of the presence of

an ARP. In addition, unlike at bricks-and-mortar stores the consumer can easily find the prices of exactly the same product charged in different stores, and not just the prices of similar products. Compared to an ERP, which is a result of consumers' external search, a seller-supplied ARP can be regarded as less credible due to the possible manipulation from the seller's side (e.g., Grewal and Compeau 1992). As a result, consumers are more likely to rely on an ERP than on an ARP if they have access to an ERP. While this effect may only apply to a limited extent at eBay auctions due to the binding role of the minimum bid and a reservation price (Kamins et al. 2004), we expect it to play an important role in name-your-own-price auctions. Therefore, we hypothesize that in NYOP an ARP does not influence the bid value in the presence of an ERP.

H6. An advertised reference price (ARP) will have no effect on the bid value in the presence of an external reference price (ERP).

In the posted-price scenario an ARP has been found to increase purchase intentions (e.g., Urbany et al. 1988) because it increases the transaction utility when compared to an actual selling price (Thaler 1985). In online interactive pricing mechanisms, however, the role of an ARP changes. In the absence of an actual selling price, a seller-provided ARP signals the value of the product but also conveys information about the expected threshold and the value required for a successful bid. Consequently, consumers with a product valuation below a seller-provided ARP are less likely to take part in the auction. The results of Kamins et al. (2004) support this notion. The authors show that in the presence of seller-supplied reference prices the number of auction participants is significantly lower. Moreover, a high ARP implying a need for a high bid value decreases consumer surplus and may therefore decrease purchase intentions. Additionally, if consumers have access to an ERP they can compare it to the ARP. Due to relatively low prices online (Brynjolfsson and Smith 2000; Zettelmeyer 2000), an ERP may be lower than an ARP and thus elicit a feeling of deception and price unfairness with respect to the seller-provided ARP. Previous research has shown that unfair price perceptions decrease purchase intentions (e.g., Campbell 1999). Therefore, we propose that presence and level of an ARP have a negative effect on purchase intentions.

H7. Presence and level of an ARP will have a negative influence on purchase intentions in name-your-own-price auctions.

3. Empirical study

The aim of the study is to analyze the effect of various reference price concepts on bidding behavior, i.e., on the bid value and purchase intentions in order to test the hypotheses developed in the previous section. To do this, we conduct a computer-assisted laboratory experiment in which participants are provided with an ARP and are allowed to search for an ERP on the Internet. Consequently, an ERP in this study results from online search conducted by the participants. In addition, we look at actual search behavior and analyze the interaction effects between an ARP and an ERP.

3.1. Methodology

Respondents were gathered in groups of 30 in a room where everyone was provided with his or her own computer with Internet access. First, participants were shown two color pictures of two products, running shoes and an mp3 player, and this was followed by the provision of product information. The products were chosen with a view to having both a search product (mp3 player) and an experience product (running shoes). Having seen the products, participants were asked to state their IRP: "How much do you expect the price of the product to be if it is not on promotion?" based on Lichtenstein and Bearden (1989) and Kalwani and Yim (1992). In addition, we asked participants how familiar they were with the respective product (1 - very unfamiliar, 5 - very familiar) (Biswas and Blair 1991). Next, we introduced respondents to the name-your-own-price auction and asked them to submit a single bid for the products, using paper and pencil conditions. We randomly assigned participants to six experimental treatments in which we manipulated an ARP for each product: (1) a plausible ARP for shoes and no ARP for the mp3 player, (2) an exaggerated ARP for shoes and no ARP for the mp3 player, (3) no ARP for shoes and a plausible ARP for the mp3 player, (4) an exaggerated ARP for shoes and a plausible ARP for the mp3 player, (5) no ARP for shoes and an exaggerated ARP for the mp3 player, and, finally, (6) a plausible ARP for shoes and an exaggerated ARP for the mp3 player. The values for the plausible ARP were set at the average level of the prices found in online and offline stores (99.99 Euros and 69.99 Euros for running shoes and the mp3 player, respectively). The exaggerated ARP was created by doubling the plausible ARP (199.99 Euros and 139.99 Euros). The results of a pre-test conducted with twenty participants confirmed the values.

The participants were given ten minutes to determine their bids. They were told that during that time they were allowed to search the Internet, but were not obliged to do so. After

submitting a bid, the participants received an additional survey with questions about their perception of believability of the ARP, i.e., (1) whether the price provided was realistic, (2) whether the price demanded was most likely to be the average market price, (3) whether the seller could be regarded as trustworthy, and (4) whether the price provided was dubious (5-point Likert scale, 1 – strongly disagree, 5 – strongly agree) based partly on Biswas and Blair (1991), Compeau et al. (2002), Lichtenstein and Bearden (1989), Lichtenstein et al. (1991), and Urbany et al. (1988). In addition, we asked about search behavior: (1) How extensively have you searched the Internet for the prices? (1 – not at all, 5 – very extensively), (2) How many websites have you visited while looking for a price? (3) How many different retailers have you checked?, and (4) What was the average price resulting from your online search? Finally, we asked about purchase intentions (1 – purchase very unlikely, 5 – purchase very likely) (Grewal et al. 1998). Altogether, 180 participants took part in the experiment (undergraduates and graduates studying at a large Western European university). One flight ticket within Europe, two vouchers for 20 Euros and eight cinema vouchers for 5 Euros were offered as an incentive to participate in the experiment.

3.2. Results

We start with the manipulation check. We use the four questions about the reference price's perceived believability to form the factor "believability" (Cronbach's alpha is equal to 0.88 and 0.90 for shoes and the mp3 player, respectively). The results show that a plausible ARP was perceived to be significantly more believable than an exaggerated ARP with both running shoes and the mp3 player ($p < 0.01$). Therefore, we conclude that our ARP-level manipulation was successful. The average reported IRP was 106.08 Euros for shoes and 74.30 Euros for mp3 player.

Among all 180 participants, 123 undertook external search in case of shoes finding an average ERP of 84.11 Euros and 114 undertook external search in case of mp3 player finding an average ERP of 68.11 Euros. Among those who undertook search, the average number of websites visited was 2.30 for shoes and 2.06 for the mp3 player. These results are higher than the results found by Johnsohn et al. (2004), who came up with an average number of websites visited of between 1.2 and 1.8, depending on the product category. The average bid value is equal to 86.72 Euros and 59.53 Euros for shoes and the mp3 player, respectively.

In order to test hypotheses H1, H2 and H3, we conduct a regression analysis. An ARP is operationalized by using dummy coding for "low ARP" (present but lower than the initial

IRP of the respondent), and “high ARP” (present and higher than the initial IRP of the respondent), with no ARP as the baseline category. The same operationalization is applied in the case of an ERP, i.e., “low ERP” (present but lower than the initial IRP of the respondent), and “high ERP” (present and higher than the initial IRP of the respondent), with no ERP as the baseline category.

In Table 1 we present the results from the regression analysis (standardized regression coefficients). As can be seen, an IRP has a positive and significant influence on the bid value for both products, which is consistent with our hypothesis H1. The results also show that when a low ERP is found, it significantly decreases the bid value for both products. However, a high ERP increases the bid value only insignificantly. Thus, results are consistent with hypothesis H2 with respect to a low ERP. Finally, we investigate the effect of an ARP. Compared to the situation in which no ARP is given, the presence of a high ARP significantly increases the bid value in the case of shoes, while a low ARP decreases the bid value only insignificantly. Therefore, our results are partially consistent with hypothesis H3 regarding a high ARP.

Table 1. Influence of the IRP, ERP and ARP on bid values.

| Independent variables | Shoes | Mp3 player |
|-----------------------|----------|------------|
| IRP | 0.34*** | 0.48*** |
| ERP_low | -0.42*** | -0.15** |
| ERP_high | 0.03 | 0.11 |
| ARP_low | -0.01 | -0.11 |
| ARP_high | 0.24*** | 0.07 |
| # of observations | 179 | 180 |
| Model significance | 0.00 | 0.00 |
| R2 | 0.25 | 0.18 |

The maximum values of the VIF are 1.43 in the case of shoes and 1.68 in the case of a mp3 player.

Regression coefficients are standardized.

* Significant at $p = 0.10$, ** Significant at $p = 0.05$, *** Significant at $p = 0.01$.

In the next step, we test hypothesis H4 and analyze the effect of different levels of an ARP on bid values (see Table 2). The results of an ANOVA show that the mean bid values when a plausible ARP is provided (80.54 Euros and 56.29 Euros for running shoes and the mp3 player, respectively) are not significantly different from the situation when no ARP is provided (78.88 Euros and 57.23 Euros for running shoes and the mp3 player, respectively). Only when an exaggerated ARP is provided, the mean bid values increase significantly (100.65 Euros and 65.07 Euros for running shoes and the mp3 player, respectively). This supports our proposition that a plausible ARP may either decrease or increase the bid values,

depending on whether it is higher or lower than the initial IRP, while an exaggerated ARP that is more likely to be higher than the initial IRP increases bid values. Indeed, a plausible ARP was higher than the IRP only for 50% (52%) of the participants, while an exaggerated ARP was higher than the IRP for 97% (92%) of the participants for shoes (mp3 player). Therefore, results are consistent with hypothesis H4.

Table 2. Influence of various levels of an ARP on bid values.

| ARP treatment conditions | Shoes | | | Mp3 player | | |
|--------------------------|----------|---------------------------|-----------|------------|---------------------------|---------|
| | Mean bid | Differences in bid values | | Mean bid | Differences in bid values | |
| No ARP | 78.88 | Plausible ARP | -1.66 | 57.23 | Plausible ARP | 0.94 |
| | | Exagger. ARP | -21.77*** | | Exagger. ARP | -7.84* |
| Plausible ARP | 80.54 | No ARP | 1.66 | 56.29 | No ARP | -.94 |
| | | Exagger. ARP | -20.11*** | | Exagger. ARP | -8.78** |
| Exagger. ARP | 100.65 | No ARP | 21.77*** | 65.07 | No ARP | 7.84* |
| | | Plausible ARP | 20.11*** | | Plausible ARP | 8.78** |

* Significant at $p = 0.10$, ** Significant at $p = 0.05$, *** Significant at $p = 0.01$.

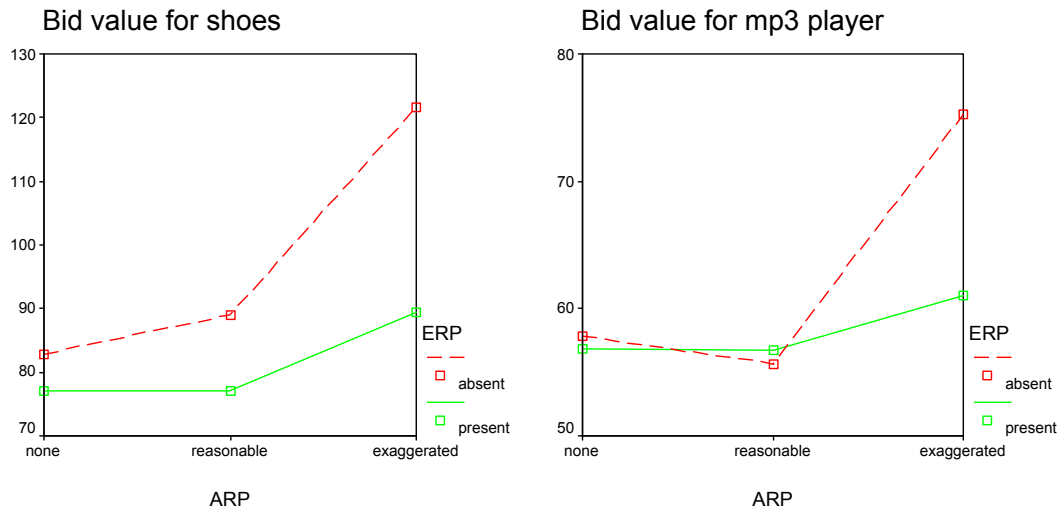
In the next step, we analyze the effect of an ARP on search behavior. In hypothesis H5 we propose that the presence of an ARP decreases consumer search. The results show that in the situation in which an ARP is provided, 68% (66%) of participants undertake external search, compared to 70% (58%) in the situation when no ARP is present for running shoes (mp3 player). The differences are insignificant. Next, we check the extent to which search is undertaken by the participants who are actually looking for an ERP (see Table 3). Contrary to our hypothesis, the search conducted is not less in the presence of an ARP. Moreover, we can see that it even increases for all the measures we used, although the increase is not significant. We also check for the differences between three conditions: no ARP, a plausible ARP, and an exaggerated ARP. The results are consistent, however, for the number of retailers: in the case of running shoes, the search significantly increases with an exaggerated ARP, but not with plausible ones. This implies that consumers may become suspicious when they see an exaggerated ARP and search even more. Results are consistent (i.e., insignificant) if we additionally control for product familiarity. Consequently, hypothesis H5 cannot be supported.

Table 3. Influence of the ARP on magnitude of search.

| Measure | ARP treatment conditions | Shoes | | Mp3 player | |
|---------------------|--------------------------|---------|---------|------------|---------|
| | | average | p-value | average | p-value |
| Extent of search | ARP Absent | 2.38 | 0.18 | 2.45 | 0.85 |
| | ARP Present | 2.59 | | 2.48 | |
| Number of websites | ARP Absent | 2.04 | 0.17 | 1.93 | 0.59 |
| | ARP Present | 2.43 | | 2.13 | |
| Number of retailers | ARP Absent | 2.00 | 0.11 | 2.55 | 0.50 |
| | ARP Present | 3.76 | | 5.08 | |

The previous results show that the majority of participants conduct external search. Since the effect of an ARP on the bid value is likely to depend on whether an ERP is present or not, we check for this possibility. Figure 1 presents the mean bid values for three experimental conditions: (1) no ARP, (2) a plausible ARP, and (3) an exaggerated ARP in the presence and absence of an ERP. First of all, we can see that in all cases but one, mean bid values are lower when an ERP is present. Additionally, the increase in mean bid values when an exaggerated ARP is provided is much lower in presence of an ERP compared to the situation when external search is not conducted. This implies that the effect of an ARP is diminished by the presence of an ERP.

Figure 1. Effect of ARP and ERP on bid values.



A more detailed analysis is presented in Table 4 which reports the results of an ANOVA where we compare three experimental treatments: (1) no ARP, (2) a plausible ARP, and (3) an exaggerated ARP for situations when an ERP was or was not found. The results show that in the absence of an ERP, an exaggerated ARP significantly increases the mean bid values by

38.68 Euros in case of shoes and 17.39 Euros in case of mp3 player. On the other hand, in the presence of an ERP the increase is much smaller (12.12 Euros and 4.24 Euros for shoes and mp3 player respectively) and only marginally significant in case of shoes and not significant in case of mp3 player.

Table 4. Interaction effects of ERP and ARP on bid values.

| ARP treatment conditions | Bid value | | | | Difference in bid value | |
|--------------------------|------------|-------------|------------|-------------|-------------------------|------------|
| | Shoes | | Mp3 player | | Shoes | Mp3 player |
| | ERP absent | ERP present | ERP absent | ERP present | | |
| No ARP | 82.89 | 77.16 | 57.84 | 56.80 | 5.73 | 1.04 |
| Plausible ARP | 88.99 | 77.11 | 55.67 | 56.71 | 11.88 | -1.04 |
| Exaggerated ARP | 121.57 | 89.38 | 75.23 | 61.04 | 32.19*** | 14.19*** |
| p-value | 0.00 | 0.08 | 0.06 | 0.49 | | |

* Significant at $p = 0.10$, ** Significant at $p = 0.05$, *** Significant at $p = 0.01$.

These results are consistent with hypothesis H6. The comparison of Table 2 and Table 4 shows how the results differ when an ERP is taken into account in the analysis and underline the importance of external reference prices for bidding behavior in name-your-own-price auctions.

Analogously, we test the interaction effects of ERP and ARP on purchase intentions to test hypothesis H7 (see Table 5). We proposed that provision of an ARP decreases the purchase intentions. The results show that a plausible ARP significantly decreases the purchase intentions for shoes when an ERP is present and for mp3 player when an ERP is absent. An exaggerated ARP consistently decreases the purchase intentions in all cases but one. This effect is stronger in the presence of an ERP and implies that when consumers conduct search and confront the real prices with an exaggerated ARP, it significantly decreases their purchase intentions.

Table 5. Interaction effects of ERP and ARP on purchase intentions.

| ARP treatment conditions | Purchase intentions | | | | Difference in purchase intentions | |
|--------------------------|---------------------|-------------------|-------------------|-------------------|-----------------------------------|------------|
| | Shoes | | Mp3 player | | Shoes | Mp3 player |
| | ERP absent | ERP present | ERP absent | ERP present | | |
| No ARP | 3.11 | 3.50 | 3.32 | 3.26 | -0.39 | 0.06 |
| Plausible ARP | 3.39 ^b | 2.95 ^a | 2.75 ^a | 3.39 ^b | 0.44 | -0.64** |
| Exaggerated ARP | 2.81 ^b | 2.38 ^a | 2.53 ^a | 2.72 ^a | 0.42 | -0.19 |
| p-value | 0.26 | 0.00 | 0.06 | 0.02 | | |

* Significant at $p = 0.10$, ** Significant at $p = 0.05$, *** Significant at $p = 0.01$.

^a - Significant change compared to an ARP absence.

^b - Insignificant change compared to an ARP absence.

4. Conclusions

New interactive pricing mechanisms in online retailing, such as name-your-own-price or eBay auctions, require consumers to submit a bid for a product and thus to indicate how much they are willing to pay for it. Such a procedure differs from the posted-price scenario, where consumers either accept or reject a seller's posted price, and it thus gives consumers more control over the transaction price. In our paper, we analyze the effects of three reference price concepts, an internal (IRP), an external (ERP) and an advertised reference price (ARP), on the bidding behavior in terms of bid value, purchase intentions and search behavior.

The results show that an IRP consistently and positively influences the bid value. This implies that consumers use the prices from their past experience, in order to determine the bid value even in the presence of external price information. In addition to an IRP, an ERP also plays an important role in the bid value determination. Our results suggest that consumers realize the benefits of easy and fast online search and look for prices in other online stores before conducting a purchase. However, an interesting pattern can be noticed in that consumers are only influenced by low ERP values, whereas high prices seem to be ignored and do not have any effect on bid values. This is consistent with the findings of Rajendran and Tellis (1994) that among various ERPs, it is the lowest price that acts as an important cue for a reference price. Taken together, our results are consistent with previous studies from the posted-price scenario that conclude that both an IRP and an ERP are important determinants of product valuation (Mayhew and Winer 1992; Rajendran and Tellis 1994).

With regard to a seller-provided reference price, opposite to Kamins et al. (2004), our results imply that it has only a limited influence on bid values in name-your-own-price auctions when controlled for an IRP and an ERP. We show that a plausible ARP has no significant effect on bid values, while an exaggerated ARP increases bid values significantly but only in the absence of an ERP. Thus, we extend the existing results from posted-price and online auction scenarios and we emphasize the importance of including the effect of an ERP in the analysis of bidding behavior.

Further we show that the effect of an ARP on search behavior and purchase intentions differs in interactive pricing scenario compared to traditional settings. In the posted-price scenario an ARP has been found to decrease the external search and increase purchase intentions. These results are, however, not replicated in the online interactive pricing scenario. First of all, we show that in the context of a name-your-own-price auction the presence of an ARP does not

decrease search as it does in the offline environment (Urbany et al. 1988). These results imply that search is more beneficial in interactive pricing mechanisms than in offline posted-price scenarios. Second, we show that in name-your-own-price auctions an ARP does not increase purchase intentions but can even decrease them. Altogether, our results show that an ARP in interactive pricing mechanism offers only limited advantages and some disadvantages for retailers. On the one hand, an exaggerated ARP increases bid values in the absence of external search. On the other hand, it significantly decreases purchase intentions. In contrast, a plausible ARP has no systematic influence on bid values and is likely to decrease purchase intentions. In presence of such results, the provision of an ARP is not recommended to name-your-own-price retailers.

We acknowledge several limitations to our study. We use an experimental setting with no purchase obligation rather than a real purchase situation. Furthermore, we realize that additional product categories would make it more feasible to generalize our results. Lastly, we focus on one specific format of interactive pricing mechanism. Future research may analyze other interactive pricing mechanisms, such as search key auctions.

References

- Bapna, R. (2005). Consumer Surplus in Online Auctions. Working Paper, University of Connecticut.
- Biswas, A. (1992). The Moderating Role of Brand Familiarity in Reference Price Perceptions. *Journal of Business Research*, 25(November), 251-262.
- Biswas, A., and Blair, E. A. (1991). Contextual Effects of Reference Prices in Retail Advertisements. *Journal of Marketing*, 55(July), 1-12.
- Bitta, A. J. D., Monroe, K. B., and McGinnis, J. M. (1981). Consumer Perceptions of Comparative Price Advertisements. *Journal of Marketing Research*, 18(November), 416-427.
- Briesch, R. A., Krishnamurthi, L., Mazumdar, T., and Raj, S. P. (1997). A Comparative Analysis of Reference Price Models. *Journal of Consumer Research*, 24(September), 202-214.
- Brynjolfsson, E., and Smith, M. D. (2000). Frictionless Commerce? A Comparison of Internet and Conventional Retailers. *Management Science*, 46(4), 563-585.
- Burton, S., Lichtenstein, D. R., and Herr, P. M. (1993). An Examination of the Effects of Information Consistency and Distinctiveness in a Reference Price Advertising Context. *Journal of Applied Social Psychology*, 23(24), 2074-2092.
- Campbell, M. C. (1999). Perceptions of Price Unfairness: Antecedents and Consequences. *Journal of Marketing Research*, 36(May), 187-199.
- Chandran, S., and Morwitz, V. G. (2005). Effects of Participative Pricing on Consumers' Cognitions and Actions: A Goal Theoretic Perspective. *Journal of Consumer Research*, 32(2), 249-259.
- Chernev, A. (2003). Reverse Pricing and Online Price Elicitation Strategies in Consumer Choice. *Journal of Consumer Psychology*, 13(1and2), 51-62.
- Compeau, L. D., and Grewal, D. (1998). Comparative Price Advertising: An Integrative Review. *Journal of Public Policy and Marketing*, 17(2), 257-273.
- Compeau, L. D., Grewal, D., and Chandrashekar, R. (2002). Comparative Price Advertising: Believe It or Not. *The Journal of Consumer Affairs*, 36(2), 284-294.
- Dholakia, U. M., and Simonson, I. (2005). The Effect of Explicit Reference Points on Consumer Choice and Online Bidding Behavior. *Marketing Science*, 24(2), 206-217.
- Dickson, P. R., and Sawyer, A. G. (1990). The Price Knowledge and Search of Supermarket Shoppers. *Journal of Marketing*, 54(3), 42-53.
- Grewal, D., and Compeau, L. D. (1992). Comparative Price Advertising: Informative or Deceptive? *Journal of Public Policy and Marketing*, 11(1), 52-62.

- Grewal, D., Monroe, K. B., and Krishnan, R. (1998). The Effects of Price-Comparison Advertising on Buyers' Perceptions of Acquisition Value, Transaction Value, and Behavioral Intentions. *Journal of Marketing*, 62(April), 46-59.
- Hardie, B. G. S., Johnson, E. J., and Fader, P. S. (1993). Modeling Loss Aversion and Reference Dependence Effects on Brand Choice. *Marketing Science*, 12(4), 378-394.
- Helson, H. (1964). *Adaptation Level Theory*. New York: Harper and Row Publishers, Inc.
- Jensen, T., Kees, J., Burton, S., and Turnipseed, F. L. (2003). Advertised Reference Prices in an Internet Environment: Effects on Consumer Price Perceptions and Channel Search Intentions. *Journal of Interactive Marketing*, 17(2), 20-33.
- Johnson, E. J., Moe, W. W., Fader, P. S., Bellman, S., and Lohse, G. L. (2004). On the Depth and Dynamics of Online Search Behavior. *Management Science*, 50(3), 299-308.
- Kalwani, M. U., and Yim, C. K. (1992). Consumer Price and Promotion Expectations: An Experimental Study. *Journal of Marketing Research*, 29(February), 90-100.
- Kalwani, M. U., Yim, C. K., Rinne, H. J., and Sugita, Y. (1990). A Price Expectations Model of Customer Brand Choice. *Journal of Marketing Research*, 27(August), 251-262.
- Kalyanaram, G., and Winer, R. S. (1995). Empirical Generalizations from Reference Price Research. *Marketing Science*, 14(3), G161-G169.
- Kamins, M. A., Dreze, X., and Folkes, V. S. (2004). Effects of Seller-Supplied Prices on Buyers' Product Evaluations: Reference Prices in an Internet Auction Context. *Journal of Consumer Research*, 30(March), 621-628.
- Krishnamurthi, L., Mazumdar, T., and Raj, S. P. (1992). Asymmetric Response to Price in Consumer Choice and Purchase Quantity Decisions. *Journal of Consumer Research*, 19(3), 387-400.
- Kumar, V., Karande, K., and Reinartz, W. J. (1998). The Impact of Internal and External Reference Prices on Brand Choice: The Moderating Role of Contextual Variables. *Journal of Retailing*, 74(3), 401-426.
- Lichtenstein, D. R., and Bearden, W. O. (1989). Contextual Influences on Perceptions of Merchant-Supplied Reference Prices. *Journal of Consumer Research*, 16(June), 55-66.
- Lichtenstein, D. R., Burton, S., and Karson, E. J. (1991). The Effect of Semantic Cues on Consumer Perceptions of Reference Price Ads. *Journal of Consumer Research*, 18(December), 380-391.
- Mayhew, G. E., and Winer, R. S. (1992). An Empirical Analysis of Internal and External Reference Prices Using Scanner Data. *Journal of Consumer Research*, 19(June), 62-70.

- Mazumdar, T., and Papatla, P. (1995). Loyalty Differences in the Use of Internal and External Reference Prices. *Marketing Letters*, 6(2), 111-122.
- Mazumdar, T., and Papatla, P. (2000). An Investigation of Reference Price Segments. *Journal of Marketing Research*, 37(May), 246-258.
- Monroe, K. B. (2003). *Pricing, Making Profitable Decisions*. New York: McGraw Hill.
- Monroe, K. B., Bitta, A. J. D., and Downey, S. L. (1977). Contextual Influences on Subjective Price Perceptions. *Journal of Business Research*, 5, 277-291.
- Rajendran, K. N., and Tellis, G. J. (1994). Contextual and Temporal Components of Reference Price. *Journal of Marketing*, 58(January), 22-34.
- Ranyard, R., Charlton, J. P., and Williamson, J. (2001). The Role of Internal Reference Prices in Consumers' Willingness to Pay Judgments: Thaler's Beer Pricing Task revisited. *ACTA Psychologica*, 106(3), 265 - 283.
- Sherif, C. (1963). Social Categorization as a Function of Latitude of Acceptance and Series Range. *Journal of Abnormal Psychology*, 67(August), 148-156.
- Spann, M., Skiera, B., and Schäfers, B. (2004). Measuring Individual Search Costs and Willingness-To-Pay via Reverse Pricing. *Journal of Interactive Marketing*, 18(4), 22-36.
- Spann, M., and Tellis, G. J. (2006). Does the Internet Promote Better Consumer Decisions? The Case of Name-Your-Own-Price Auctions. *Journal of Marketing*, 70(1), 65-78.
- Thaler, R. (1985). Mental Accounting and Consumer Choice. *Marketing Science*, 4(3), 199-214.
- Urbany, J. E. (1986). An Experimental Examination of the Economics of Information. *Journal of Consumer Research*, 13(September), 257-271.
- Urbany, J. E., Bearden, W. O., and Weilbaker, D. C. (1988). The Effect of Plausible and Exaggerated Reference Prices on Consumer Perceptions and Price Search. *Journal of Consumer Research*, 15(June), 95-110.
- Winer, R. S. (1986). A Reference Price Model of Brand Choice for Frequently Purchased Products. *Journal of Consumer Research*, 13(2), 250-256.
- Zettelmeyer, F. (2000). Expanding to the Internet: Pricing and Communication Strategies When Firms Compete on Multiple Channels. *Journal of Marketing Research*, 37(3), 292-308.