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Trends in the Behavioral Sources of Customer Profitability and the Role of Flat-Rate Pricing

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Summary

The paradigm shift that relationship marketing constitutes entails a change in perspective from a static transaction-focus to a dynamic and long-term relationship orientation. In this regard one of the most fundamental considerations concerns the trend in customer profitability over the course of the relationship duration. The prevailing tenet is that customers become more profitable over time and, consequently, that customer lifetime maximization is a key aspect of marketing. This message of marketing research, textbooks, and management literature alike has remained basically unchallenged for the past 15 years. The present work reviews this notion of increasing profitability, focusing on the underlying customer behavioral sources of profitability. In a brief survey of prior research, it is shown that despite the broad proliferation of this tenet, a considerable amount of findings and theories still conflict.

In an effort to provide greater clarity towards generalization, in this work a rigorous cross-industry empirical analysis of the development of the behavioral sources of customer profitability over time is conducted. This study is based on six customer datasets in consumer markets over a multiyear period. Four datasets are in non-contractual contexts such as airline (n=11,218), hardware store (n=20,146), fashion retailer (n=18,675), and general merchandise retailer (n=29,221); and two datasets are in contractual contexts such as telecommunications company (n=6,875) and internet service provider (n=33,675). In contrast to the prevailing belief, churn rates are found to increase and customer activity and spending is found to attenuate over time, indicating a general decreasing trend in profitability.

In a subsequent step, this work examines the viability of flat-rate tariffs as a strategy to counter this decreasing trend. While first companies facing customer

revenue erosion report the use of these tariff structures to stabilize revenues, the viability of this strategy has received considerable dispute. At first glance, firms seem to benefit from constant revenues. However, the decreasing trend further adds to the ubiquitous phenomenon of flat-rate bias, i.e., that customers chose a flat-rate even if pay-per-use would be less expensive for them. Whereas prior research finds no negative impact of flat-rate bias on customer loyalty, the present study provides a more differentiated perspective. A survival analysis of the internet service provider's transactional data shows that the expected lifetime of a flat-rate biased customer decreases with every overspend Euro by about one percent.

The results of an experimental study among mobile telephony customers furthermore indicate that the competitive position of a service provider moderates the consequences of flat-rate bias and explains these converse findings of existing research. While low-cost service providers only experience increased tariff switching, premium providers are confronted with an increased churn risk. Therefore, managers of premium service providers considering flat-rates as a strategy to stabilize revenues are advised to carefully evaluate reactions of their flat-rate biased customer base and potentially proactively manage customers with strong flat-rate bias. Low cost providers, however, are in no need for action and can benefit from flat-rates without the danger of churn.

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List of Abbreviations

AFT	Accelerated Failure Time
AIC.....	Akaike Information Criterion
Avg.....	Average
CE.....	Customer Equity
CI.....	Confidence Interval
CLV	Customer Lifetime Value
CRM	Customer Relationship Management
DCF	Discounted Cash Flow
DF	Degrees of Freedom
EPS.....	Earnings per Share
FR.....	Flat-Rate
FRB	Flat-Rate Bias
HR	Hazard Ratio
ISP	Internet Service Provider
K-S Test.....	Kolmogorov-Smirnov Test
NPV	Net Present Value
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
OR	Odds Ratio
PH	Proportional Hazard
PP.....	Percentage Point
PPU	Pay-Per-Use
PSM.....	Price Sensitivity Meter
Qtrs	Quarters
ROE.....	Return on Equity
Telco	Telecommunications Company

1 Introduction

1.1 Research Motivation

1.1.1 General Trends in Customer Profitability

One of marketing's fundamental explananda is the behavior of buyers in consummating exchanges, which originates marketing science's aim to explain "why do which buyers purchase what they do, where they do, when they do, and how they do" (Hunt 1983, p. 13). At this, the tenet in relationship marketing that customers become more profitable over time enjoys widespread acceptance in academic research (Blattberg et al., 2009; V. Kumar and R. Venkatesan, 2005; Reinartz and V. Kumar, 2003), textbooks (Bruhn, 2002; Kotler and G. Armstrong, 2010), and managerial guides (Hughes, 2006; Reichheld and Teal, 1996; Schenck, 2005). Also in practice, this proposition has found its way into general directives that serve to steer several corporate functions and that managers widely use as a foundation for marketing strategy formulation and its justification for shareholders (CQ Transcriptions LLC, 2010a; b; c).

This notion of increasing customer profitability was established mainly in the early 1990s, most noticeably through Reichheld and Sasser's (1990) and Reichheld and Teal's (1996) findings (see Figure 1). The underlying arguments for this claim are that (1) customers become more loyal to the company over time and, thus, are less prone to defection (Fielding, 2005; Hughes, 2006; Schmittlein and R. A. Peterson, 1994); (2) customers familiarize themselves with the products of the company over time and, hence, use them more frequently, while also discovering this company's other products (Borle et al., 2008; V. Kumar and R. Venkatesan, 2005; Reichheld and Sasser, 1990; Reichheld and Teal, 1996; Reinartz and V. Kumar, 2003); (3) customers with long-lasting relationships are less price sensitive and, therefore, price premiums can be realized (Reichheld and Sasser, 1990;

Reichheld and Teal, 1996; Reinartz and V. Kumar, 2003); (4) loyal customers generate new sales through word-of-mouth referrals (Reichheld and Sasser, 1990; Reichheld and Teal, 1996; Reichheld, 2003); (5) potential acquisition costs can be recovered over a longer period (Heskett et al., 1990; Reichheld and Sasser, 1990; Reichheld and Teal, 1996); and (6) the mutual familiarity between customers and the company enables greater efficiency and, as a result, decreases costs of servicing these customers (Heskett et al., 1990; Reichheld and Sasser, 1990; Reichheld and Teal, 1996).

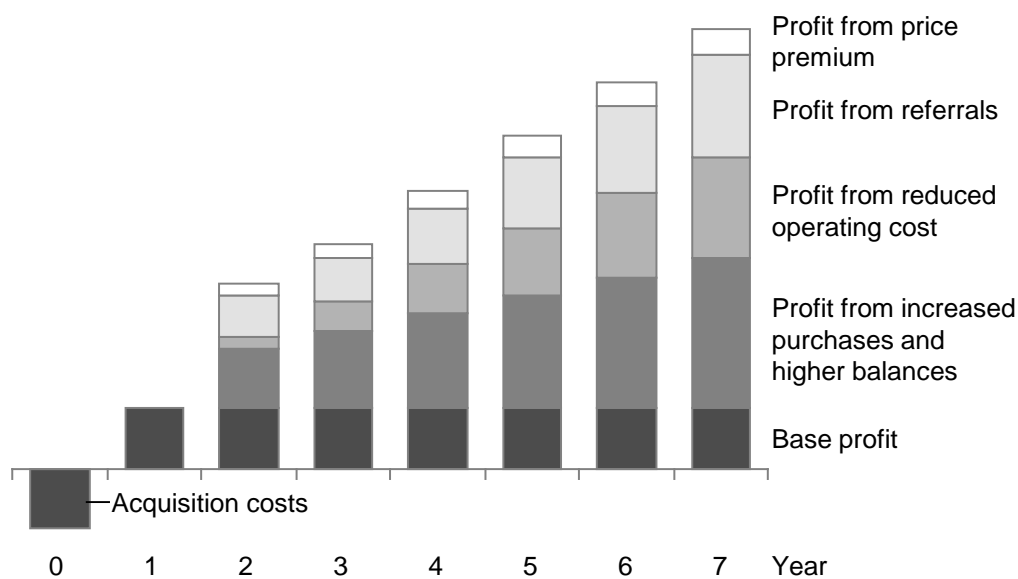


Figure 1: Reichheld and Sasser's Illustration of Customer Profits Over Time
Source: Reichheld and Sasser (1990)

With the proliferation of information technology-based customer relationship management systems and the increasing availability of data, a plethora of studies further investigating the sources of customer profitability over time has followed. Many of these studies support the original claims of Reichheld and his colleagues (Reinartz and V. Kumar, 2003; Reichheld, 2003; Fielding, 2005), but there is also a considerable amount of research that conflicts with their findings (Borle et al., 2008; Li, 1995; Reinartz and V. Kumar, 2000a). Additionally, existing studies on the development of customer profitability differ widely in research methodology. Some address profitability only as an aggregate or focus on a specific subset of its antecedent behavioral sources (Bolton et al., 2004); others are based on a small number of customer datasets from particular contexts, thus, exhibit more of a case

study character. Some critics have even argued, that existing research is "highly selective and all too frequently designed to support a particular [...] perspective" (Egan, 2001, p. 375; Fernandes and Proença, 2008), which they attribute to the enormous popularity of relationship marketing and academics' "lemming-like" devotion (S. Brown, 1998, p. 171).

In fact, e.g. in the telecommunications industry, where customer retention and churn management traditionally plays a central role, a positive effect of long customer lifetimes on profitability is not observable: Figure 2 shows the average customer lifetime duration and profitability (EBITDA-margin) of 50 mobile operators worldwide. As can be seen, a clear-cut positive correlation between the firms' average customer lifetime durations and their profitability, which the original tenet would suggest, does not exist.

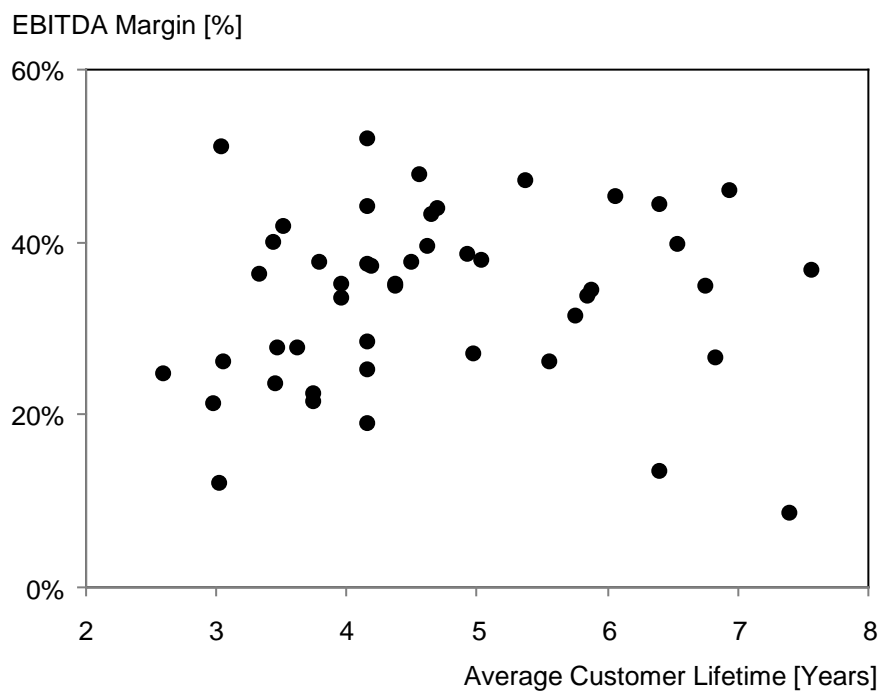


Figure 2: Average Customer Lifetime Durations and Profitability of 50 Mobile Operators
Source: Own Illustration on the Basis of Companies' Annual Reports

The need for further research is continuously pointed out in many review or research agenda papers. For example, Jain and Singh (2002, p. 44) highlight in their 'review and future directions' on customer lifetime value research that existing findings still conflict and note that "clearly more research is needed to investigate these differences in [these] findings". Likewise, Verhoef and Langerak

(2002, p. 73) warn "that it is a gross simplification to equate loyal customers with higher profits." As a consequence, Blattberg, Malthouse, and Neslin (2009) conclude in their landmark study on the generalizability of these proposition, that ambiguity remains. Furthermore, they point to the need for further research before many findings can be generalized. Also, Kumar and colleagues (2006, p. 91) highlight in their introduction to a special issue on managing customers for value of the *Journal of Service Research*: "Several of the articles identify the need for additional research to understand the dynamics of customer behavior. Models and metrics need to be dynamic in nature [...]. Our models and theories need to include the notion that customers change over time."

1.1.2 Consequences of Flat-Rate Bias

The trend in customer profitability is not just of purely academic interest, in that it is not only a given constant, which marketing managers are to fatalistically incorporate in their projection of customer revenues. In fact the opposite is true since a firm's marketing actions are reciprocal with customer behavior (see Figure 3). Its brand concept, product design, or orchestration of the marketing mix cause affective responses, attitudes, and, ultimately, behavior of the consumers such as the purchase or use of the product—which in turn serve as input for a companies' marketing activities (Blattberg et al., 2009; S. Brown, 1998; Epstein et al., 2008; Heskett et al., 1994). Therefore, a review of customer behavior inherently entails implications for other marketing functions.

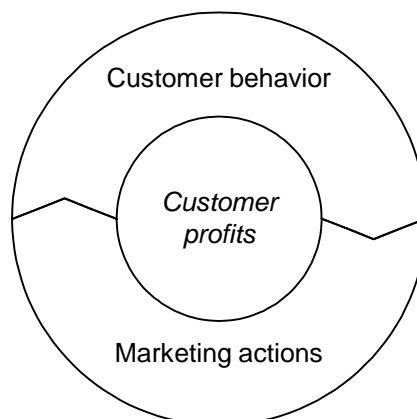


Figure 3: Reciprocity of Customer Behavior and Marketing Actions
Source: Own Illustration

In particular, Reichheld and Sasser's ubiquitous illustration (see Figure 1) of how additional profits from ever increasing purchase frequency, spending levels, price premium, referrals, and reduced cost of servicing the consumer over time add up to a multiple of the initial base profit is still fixed in many marketing managers' minds and serve as rationale for many marketing strategies. A very prominent example is pricing because it can be directly influenced by a company. Here, the notion of increasing willingness to pay and decreasing price sensitivity is often cited as guiding principle (Mitchell and Vogelsang, 1991; Reichheld and Teal, 1996, p. 49; Yadev and Berry, 1996). In particular the flat-rate pricing scheme, which is becoming increasingly popular across many industries, has received considerable dispute against this background. Critics argue that by fixing customer revenues, flat-rate tariffs are foregoing significant profit potential because they do not capitalize on the users' increasing usage frequency and willingness to pay (Butcher, 2010; K. P. Hwang and Fang, 2009; Openet, 2010; Suoranta and Lappeteläinen, 2010). However, in some industries first firms are reporting the successful use of flat-rates as a strategy to counter the customer revenue erosion which they are witnessing (Dellis, 2009; TF Investext, 2010; Thomson Reuters, 2005).

In contexts with eroding customer revenues, flat-rate tariffs have another interesting property that, so far, has not yet received any attention in scientific research. By the stabilization of revenues with flat rate pricing, the decreasing trend adds to the phenomenon of flat-rate bias, i.e. that flat-rate customers chose a flat-rate even if a pay-per-use tariff would be more economical for them. Several studies find that consumers show tariff specific preferences that may lead them to choose a tariff that does not minimize their bill (Della Vigna and Malmendier, 2006; Heidenreich and Handrich, 2010; Lambrecht and Skiera, 2006; Nunes, 2000). Going back to the reciprocity of firm actions and customer behavior, the question then must be asked whether this can be sustainable. If customers become aware of paying too much with their flat-rate, economic theory predicts that they will switch to a cheaper alternative (Khan et al., 2004). This can be achieved either by switching the tariff within the service provider or by churning to a competitor. Since customer loyalty is one of the key concerns in marketing practice (S. Gupta et al., 2004; Reichheld and Sasser, 1990; Reichheld, 2003), managers are left with the fundamental question whether flat-rate biased customers are endangered and

need to be proactively managed, or no reaction is needed and firms can benefit from constant revenues at a higher level.

Despite this high managerial relevance, only one study so far investigates the consequences of flat-rate bias on customer behavior (Lambrecht and Skiera, 2006) and finds no implications for customer loyalty. This is however in conflict with other studies on tariff choice showing that, in general, customers who have chosen the economically right tariff, have higher retention rates than customers who have chosen the wrong tariff (Joo et al., 2002; Wong, 2010b). This seems plausible as customers who become aware of the wrong tariff choice might not only question their tariff but also their provider to whom they potentially attribute this failure (C. Peterson et al., 1982; Riess et al., 1981). As the attractiveness of competitive offers is the main driver of customer loyalty (Morgan and Hunt, 1994), customers will churn if they find cheaper tariffs in the market.

The potential savings by competitive offers are contingent on the market position of the service provider. Low-cost providers try to offer their services at the lowest price in the market or at least the lowest price to value ratio (Porter, 1980). Premium service providers focus on differentiation and have rather high prices (Porter, 1980) leaving more space for potential savings from competitors. This differentiation of the consequences of flat-rate bias by the competitive position of the service provider could therefore resolve the discrepancy between Lambrecht and Skiera's findings (2006) and evidence from general research on tariff choice.

1.2 Research Questions and Objectives

This dissertation aims to extend marketing research in two dimensions: insights on the dynamics of customer profitability over the course of the relationship in consumer contexts (research gap 1); as well as the sustainability of flat-rate bias and the moderating role of a firm's competitive position (research gap 2). These two general objectives can be further divided into three concrete research questions.

First, I aim to review generally held contentions on the trend in the development of customer profitability over time. Though, profitability as an aggregate is ultimately the outcome of interest, as an abstract measure it is hard to be operationalized for marketing managers. In an aim for a holistic, consistent, and actionable analysis, I therefore direct my analysis towards the customers' behavioral sources of profitability as focal construct—i.e., relationship length, purchase frequency, spending levels, and cross buying (Bolton et al., 2004).

RQ1: Do the customers' behavioral sources of profitability change over the course of their customer relationship duration and, if so, does this trend have a positive or negative effect?

My second objective is to investigate consequences of flat-rate bias on customer loyalty. So far only one study on the consequences of flat-rate bias exists which finds no impact of flat-rate bias on churn. This however contradicts general tariff choice research which predicts negative impact of suboptimal tariff choice on customer loyalty.

RQ2: Does flat-rate bias increase tariff switching and customer churn?

This dissertation should also cater practitioners. Therefore, in this context this work is also concerned with the customer lifetime value impact of flat-rate bias, which potentially acts on two drivers of customer lifetime value—height of cash flows and customer lifetime—with oppositional effect.

Finally and third, in an effort to resolve conflicts in existing evidence, I furthermore aim to investigate whether the market position of the service provider acts as a moderator of flat-rate bias consequences (i.e., the type of consequences)?

RQ3: Is the market position of the service provider a moderator of flat-rate bias consequences?

1.3 Proceedings

Since all research questions of this dissertation concern the relationships of firms with their customers, this dissertation can draw from the large body of literature on relationship marketing. Chapter 2 gives an introduction in this field, starting with a brief summary of the evolution of relationship marketing which leads to present relationship marketing's value orientation. While the value of customer-firm relationships for firms is rather evident, insights in the motivations of consumers for relational patronage are still limited. Here, authors often cite basic economic and behavioral theories as an explanation, which has, however, received considerable dispute with regard to applicability and validity in consumer contexts (Christy et al., 1996; Egan, 2001; Fernandes and Proença, 2008). Because an understanding of the basic underlying concepts and mechanisms is indispensable in the context of this dissertation (Sheth and Parvatiyar, 1995a), I will introduce and discuss their applicability and mechanisms for and against relationship orientation of consumers. Finally, I conclude by introducing the dynamic perspective on customer relationships and highlighting conflicting findings in a meta-analysis of past research findings on the development of customer profitability over time.

Following up on these conflicting findings, Chapter 3 is dedicated to answering the first research question regarding the trend in customer profitability. Specifically, I derive several sub-questions based on a decomposition of customer profitability according to its behavioral sources and discuss past research thereon. Next, I develop my empirical research design, present my findings, and finally discuss their implications.

Chapters 4 and 5 are dedicated to the second research gap. Since this research gap addresses a specific field of marketing (pricing), in Chapter 4 a further introduction to relevant research background on pricing and, in particular on tariff choice theory and causes and consequences of flat-rate bias is given. Building on this theoretical grounding, I develop concrete hypotheses and present two studies in Chapter 5: an empirical study of transactional data to investigate consequences of flat-rate bias on customer loyalty (RQ2) as well as an experimental study to test the moderating role of the provider's competitive

position (RQ3). I conclude with a discussion of these findings and their implications.

This dissertation ends with a summary and discussion of its central findings and implications in Chapter 6.

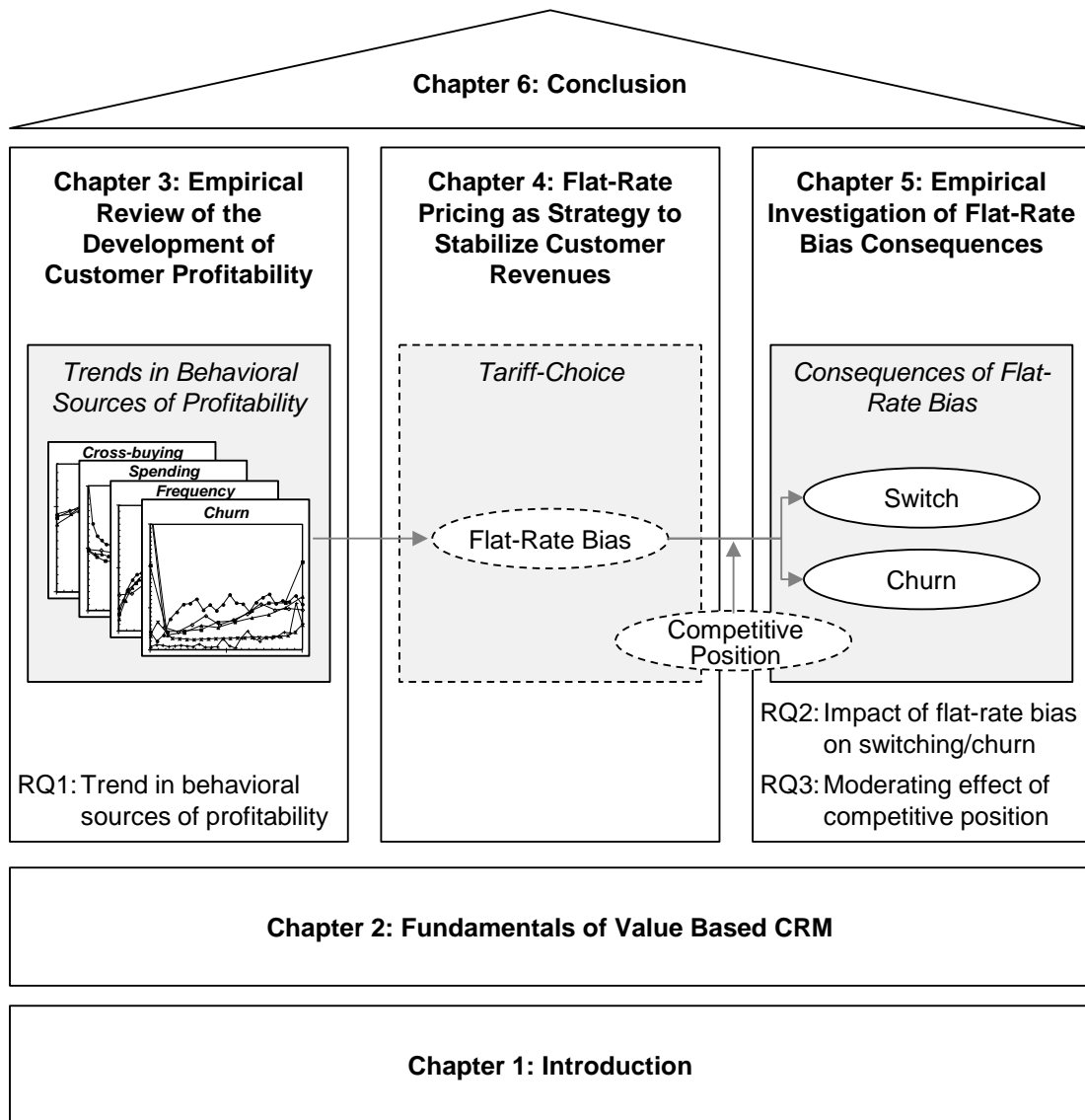


Figure 4: Structure of this Dissertation
Source: Own Illustration

2 Fundamentals of Value Based CRM

2.1 Introduction

Most marketing considerations do not aim at an isolated customer action but are implicitly or explicitly embedded in a series of interactions and mutual experiences—i.e., the *relationship*—of the firm and its customers. Products for example are designed to the customer's satisfaction in order to trigger repeat purchases; many pricing strategies explicitly take account of ongoing and repeated consumption; promotion often bases on customer purchase pathways; and many distribution strategies aim at accompanying the customer throughout his different situations in life. Likewise, also the focal constructs of this dissertation—customer profitability and flat-rate tariffs—reside in the context of these customer-firm relationships.

While the concept of the customer-firm relationship is not new, the respective accentuation in marketing theory and practice is (Sheth and Parvatiyar, 1995b). This shift in perspective from a product-centric transactions view to the management of relationships in the 1980s has led to a burst of interest and terms such as relationship marketing, customer relationship management, customer lifetime value etc. to become some of the most popular buzzwords in marketing (Verhoef and Langerak, 2002). In this regard, some critics argue that this ubiquity and popularization has led to a lose understanding of the concept (Coviello et al., 1997) and question the extent to which robust theories have been developed (Gummesson, 1997; Sheth, 1998). Therefore, this chapter is dedicated to giving a thorough introduction to these concepts starting with a historical perspective and proper definitions. Then the rational and motivation for relational engagement, both from the perspective of a firm (i.e., the value of customer relationships) and the customer (i.e., from a behavioral point of view), are discussed. Finally the

chapter concludes by discussing dynamic aspects in the development of customer relationships.

2.2 Contemporary Relationship Marketing

2.2.1 Evolution of Relationship Marketing

In recent years, many authors have proclaimed that with the change in marketing orientation from transactions to relationships, relationship marketing constitutes a new paradigm¹ (Berry, 1983; Gummesson, 1997; Parvatiyar and Sheth, 1994; Srivastava et al., 1998). Though relationship marketing has emerged as a separate domain in marketing as a scientific discipline only in the 1980s, many authors have made a compelling case that in marketing practice, relationship focus is in fact a rebirth of trade customs of the pre-industrial age (Palmatier, 2008; Sheth and Parvatiyar, 1995b). But if relationship marketing is just old wine in new bottles, the recent explosion of interest in this topic as manifested in a burst of research papers, textbooks and managerial guides defies explanation. To answer this fundamental question of what relationship marketing actually is and how it impacts marketing thought and practice, I follow this argument and first take a historic perspective to investigate the roots of relationship marketing².

Prior to the industrialization, economy was characterized by agriculture and the trade of art and artifacts, where producers performed as manufacturers as well as retailers. Most trade took place in local markets where farmers and craftsmen sold their products directly to end users. In the absence of institutionalized regulations and protection, producers and consumers formed relationships to provide the trust and business norms for their transactions. Similarly, relationships also provided confidence among merchants in the trade of products not locally produced.

¹ Though there exists some dispute whether relationship marketing really consists a new paradigm (see for example Egan, 2001).

² For an extensive review refer to Palmatier (2008) and Sheth and Parvatiyar (1995b), on which this discussion bases in parts.

With the advent of industrialization came the separation of the producers from the consumers. Economies of scale motivated manufacturers to produce in mass confronting them with an increasing complexity in 'marketing' their products. As production volumes soared at increasingly centralized production, marketing of these voluminous goods required transportation, storage, and sales across a larger geographical area and customer base to dispose of them (Palmatier, 2008, p. 8). This market condition gave rise to the new role of middlemen, who specialized in the distribution of goods, bearing the risk and costs of inventory—i.e., to "create time, place and possession utility" (Alderson, 1954, p. 13)—to match the mass production with mass consumption. The competition of these new channels with similar or indistinguishable products led to aggressive sales and promotions—and exchange to become more transactional with pricing being the salient component of the offering. In this situation, marketing as a discipline emerged³. Being organized mostly around the institutional and functional school of thought, at the center of the scientific attention were the functions performed by wholesalers and retailers (Sheth et al., 1988). Shaw (1912, p. 84) for example defined the marketing problem as "(1) to arouse a maximum of demand and (2) to supply that demand with a minimum of leakage."

Over the years, marketing discipline further evolved by integrating psychological and sociological viewpoints (see Figure 5). In fact, already in 1958 Alderson recognized the basic notion underlying relationship marketing and postulated that because people are involved, marketing "must not hesitate to draw upon the concepts and techniques of the social sciences for the enrichment of its perspective" (Alderson, 1958, p. 18). Most notable is probably the influence of sociologic and social psychological approaches on the institutional economics' 'rational-minds' theory that lead to *exchange relationships* becoming the core of marketing in the 1970s (Kotler, 1972). Though these approaches already acknowledge the relationship aspects and the importance of understanding its impact on human behavior, in essence still the focus on the unit of exchange and hence the transactions logic prevailed (Palmatier, 2008, p. 9). Consequently, also the product-centric marketing-mix management and the Four-Ps model remained

³ The first courses on the subject of marketing were offered at the University of Michigan in 1902 and at the Ohio State University in 1906 (Bartels, 1976).

the dominant paradigm for marketing thought, research, and practice for almost 40 years after its introduction around 1960 (Grönroos, 1994).

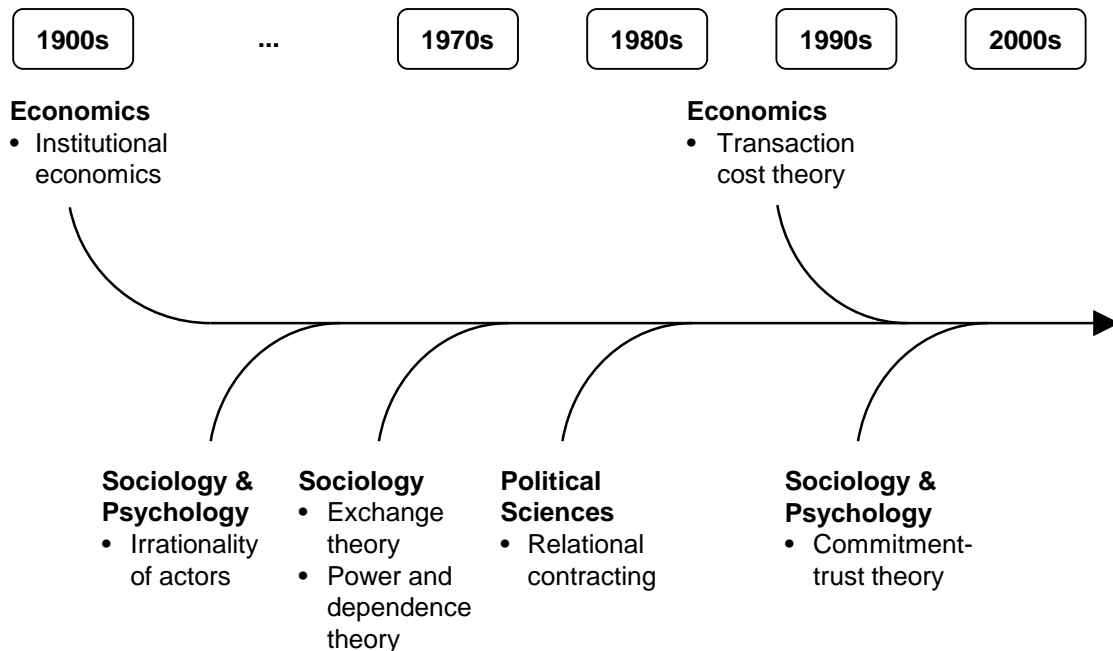


Figure 5: Evolution of Relationship Marketing Theory

Source: Own Illustration

It was only with the convergence of several market trends that research and practitioners refocused on what can be considered the heart of exchange: the interaction between the involved parties. The fundamental transformation from a sellers' market to a buyers' market in the 1970s caused consumers instead of distributors or products to become the focus of marketing attention (Kotler, 1972; Sheth and Parvatiyar, 1995b). Intense competition, critical, demanding, and educated customers and increasing churn rates in more and more transparent markets drove companies to focus on customer retention and loyalty (Sharpiro, 1993).

Another key trend can be seen in the shift to service economies, since in contrast to products, services have several traits that make relationships more important for the exchange (Vargo and Lusch, 2004): Services oftentimes have a significant cooperative component, where extended interactions of the consumer with systems, resources, or employees of the service provider is typically an intrinsic part of the production process. Also, due to the intangibility of services, they are

harder to evaluate, more perishable, and complex which makes the benefit of trust more important. Additionally, services are usually produced and delivered by the same organization, removing the need for middlemen and further reinforcing the relationship of provider and consumer.

Similarly, spurred by total quality management initiatives, individual empowerment in organizations and collaborations, new collaboration forms such as joint ventures that share resources and jointly develop ideas and products or carry out advertising campaigns arose. These relationships are devoid of any implicit or explicit expectation of exchange. Thus they could not sufficiently be explained from an exchange driven view (Parvatiyar and Sheth, 1994).

And lastly, technological advances, i.e., computerized communications and logistics systems, enabled direct transactions between producer and consumer. Functions performed by middlemen can now be undertaken by either the producer or the consumer or entirely be eliminated (Messner, 2005).

Much of this reasoning originated from inter-organizational and service marketing, where relationship marketing emerged as a popular alternative already in the 1980s. Though academics pointed out that also consumer markets could benefit from relational bonds which could lead to reliable repeat business (Dwyer et al., 1987; Goldberg, 1988; Levitt, 1983), aside from top-down approaches⁴ of direct and database marketing, relationship marketing only slowly gained acceptance with consumer marketers (O'Malley and Tynan, 2000). This domain was considered different both conceptually and contextually mostly due to the sheer size of consumer markets, the nature of competition, the anonymity of consumers, and the limited interaction between the consumers and the firm (Christy et al., 1996; O'Malley and Tynan, 2000). The fundamental ideas of relationship marketing became popular in consumer marketing only in the mid 1990s spurred by the availability of IT-supported customer contact techniques and, even more importantly, the establishment of the link between consumer

⁴ See for example Shani and Chalasani (1992) for a discussion of relationship marketing's bottom-up approach (i.e., finding products for consumers) as opposed to database marketing's top-down approach (i.e., finding consumers for products) which is still focused at the immediate sale.

behavior and relationship marketing research in academic literature (Christy et al., 1996; M. J. Evans et al., 1995; Goldberg, 1988; O'Malley and Tynan, 2000). From this discussion, two things become evident. First, the (re-)emergence of relationship marketing is due to a confluence of factors. From a seller's perspective, probably most important for their reorientation towards relationships is their aspiration of relationship-based loyalty. Second, relationship marketing can draw from a rich theoretical grounding, because the concept of relationships has been studied from scholars of several disciplines. However, this heterogeneity in background also paints a picture of the complexity of this domain, even to the extent of diverging conceptions of the term 'relationship marketing' and related concepts. This has led to this term being used rather loosely resulting in frustration for both academics and practitioners (Coviello et al., 1997). In an effort to provide more clarity, the following section discusses different interpretations and definitions of relationship marketing and develops a common understanding as base for this dissertation.

2.2.2 Definition of Relationship Marketing

The term 'relationship marketing' was first used by Barbara Bund Jackson⁵ in an industrial context in the late 1970s (Gummesson, 1997; Jackson, 1985). In most of the literature, the term is however accredited to Berry (1983, p. 25), who first introduced it in a service context as "attracting, maintaining, and enhancing customer relationships". Since then a plethora of definitions has been given, reflecting the popularity and variety of academic backgrounds. In fact, in a review of 117 academic contributions, Harker (1999) found 26 substantially different conceptualizations⁶. Probably most the influential was however given by Grönroos (1991, p. 8) who defines the goal of relationship marketing as "to establish, maintain and enhance relationships with customers and other parties at a profit so that the objectives of the parties involved are met." Table 1 shows an overview of selected definitions.

⁵ Barbara Bund Jackson is recorded as having used the term in her project on industrial marketing in the late 1970s (Gummesson, 1997).

⁶ Interestingly, most of these refer to *relationships* without defining such term, hence are somewhat tautological. At this I want to refer to Czepiel (1990, p. 13) who defines a relationship as "the mutual recognition of special status between exchange partners".

Table 1: Selected Definitions of Relationship Marketing Adapted from Bruhn (2002)

Author	Definition
Berry, 1983	Relationship marketing is attracting, maintaining, and enhancing customer relationships.
Jackson, 1985	[Relationship marketing is] marketing to win, build, and maintain strong, lasting relationships with industrial customers.
Grönroos, 1991	The goal of relationship marketing is to establish, maintain and enhance relationships with customers and other parties at a profit so that the objectives of the parties involved are met. This is achieved by a mutual exchange and fulfillment of promises.
Morgan and Hunt, 1994	Relationship marketing refers to all marketing activities directed towards establishing, developing and maintaining successful relational exchanges.
Sheth and Parvatiyar, 1995b	Relationship marketing is a marketing orientation that seeks to develop close interactions with selected customers, suppliers and competitors for value creation through cooperative and collaborative efforts.
Gummesson, 1996	Relationship marketing is marketing seen as relationships, networks and interaction.
Parvatiyar and Sheth, 2001	Relationship marketing is the ongoing process of engaging in cooperative and collaborative activities and programs with immediate and end-user customers to create mutual economic value, at reduced cost.

From the definitions in Table 1 can be seen that relationship marketing seems to comprise three constituent aspects, i.e., in discrimination to the exchange relational view on marketing (Palmatier, 2008).

1. *Time horizon:* Relationship marketing is a continuous stream of constructive interaction in which the exchange of value, if any, is not the climax but merely an interstage (Levitt, 1983). In particular, it is engaged across all stages of the customer life.
2. *Locus of value creation:* Relationship marketing evaluates its success not only from the perspective of the implementer but aims to generate benefits for all involved parties. Though the unidirectional perspective appears most relevant, relationship marketing acknowledges that the mutual

generation of value is a prerequisite for long-term relationships and hence a means to increase its effectiveness.

3. *Scope of stakeholders*: Most definitions extent the scope of relationship marketing's targets beyond customers and specifically include also relationships with suppliers, service providers, channel members, and even competitors.

In this dissertation, however, I constrain my focus with regard to the last aspect (stakeholders) and only concentrate on customer relationships. This is today widely referred to as *customer relationship management* (CRM; Reinartz et al., 2004). Despite the ubiquitousness and proliferation of the term 'CRM'⁷, there seems to be many discrepancies about what it precisely is, even to the extent that the actual meaning of the acronym CRM is contested (Buttle, 2008, p. 3). Some of these discrepancies can be explained by considering that CRM evolved from two entirely different trends from two science disciplines: (1) in marketing, the transition from a transaction to a relationship orientation, as discussed; and (2) in computer science, the development from information management to customer knowledge management (Messner, 2005). Accordingly, the definitions either emphasize the value creation and strategic importance of customer relationships or the technological aspect, i.e., collecting, storing, and processing data to enable marketing on the basis of knowledge of the needs and behavior of the individual customer (see Figure 6).

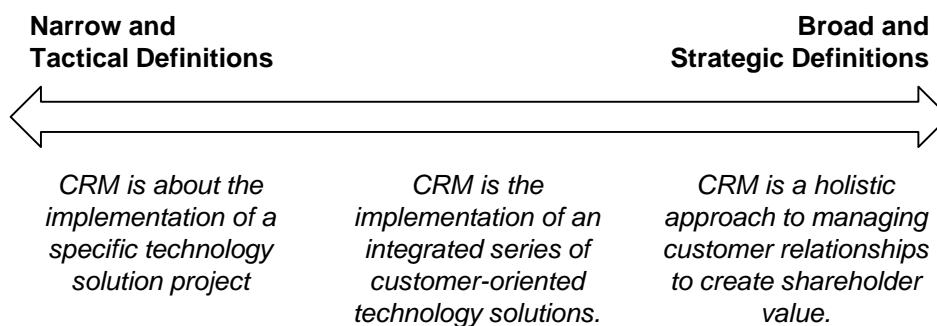


Figure 6: CRM Continuum
Source: Payne and Frow (2005)

⁷ For a detailed discussion of definitions and understandings of 'CRM' see Buttle (2008, p. 4).

In the context of this dissertation the focal aspect is strategic. Therefore, I follow an according and widespread definition that bases on Buttle (2001, p. 53):

CRM is about the development and maintenance of long-term, mutually beneficial relationships with strategically significant customers.⁸

The resemblance of this definition with Grönroos' definition of relationship marketing is not coincidental, but rather reflects its genealogy. Or as Palmatier (2008, p. 7) put it, "customer relationship management (CRM) is the managerially relevant application of relationship marketing". This definition, hence, makes also explicit the efficiency principle which is already inherently contained in the term 'management' as part of CRM: the orientation on value, which Parvatiyar and Sheth (1994, p. 1) describe as marketing "that seeks to develop and maintain interactions with selected customers for value creation through cooperative and collaborative efforts". Against this background, the systematic analysis of customer profitability and customer value is irremissable. This value perspective will be discussed in the next section.

2.3 Value Orientation in CRM

2.3.1 Value-Based Management and Customer Relationships

Over the last two decades the shareholder value planning approach has become the overarching principle to measure corporate success. Though not undisputed⁹, many researchers made a compelling case, that this orientation in the corporate decision process towards the (financial) interests of the shareholders is almost unchallengeable (Doyle, 2008, p. 3). In the main this is even endorsed by the OECD's Principles of Corporate Governance (OECD, 1999, p. 4). The shareholder value planning approach bases on two fundamental assumptions. The first is the somewhat philosophical assertion that it is the company's managers' primary

⁸ Though this definition is often used citing a quote from Buttle (2001), it is in fact a synopsis of a paragraph in his article defining CRM.

⁹ Opponents often criticize that to focus on shareholder value will lead to short-term profit orientation and that also other stakeholders of the firm should be considered (see for example Bratton 2002; Rossouw 2005).

obligation to act in the interest of its shareholders and maximize the firm's economic value. The second assumption is rather technical and refers to how this is achieved in practice. It states that the company's stock market value is based on the investors' expectation of its future cash-generating abilities. Hence, maximum economic value of a company follows from maximizing the value of future cash flows (Doyle, 2001).

From the second assumption derives that traditional backward looking accounting metrics, such as *earnings per share* (EPS) or *return on equity* (ROE) are inadequate for measuring performance. These metrics have been shown to be an unreliable indicator of a company's economic value or changes herein, due to their subjection to differing and to some extent arbitrary accounting regulations, their exclusion of investments, and their negligence of the time value of money and associated risks (Blyth et al., 1986; Rappaport, 1981, 1994). Rather should investments be assessed by their "net present value of all future cash flows expected to accrue to the firm" by means of the *discounted cash flow* (DCF) method (Rappaport, 1994, p. 51). The DCF method determines the *net present value* (NPV) of an investment by discounting all future cash flows to its present value including a potential residual value after the forecast period and accounting for risk and cost of capital by a risk-adjusted discount rate (Blyth et al., 1986):

$$NPV = -C_0 + \sum_{t=1}^n \frac{C_t}{(1+i)^t} + \frac{rv}{(1+i)^n} \quad (2.1)$$

where

t = period index,

n = planning horizon,

C_0 = initial investment,

C_t = cash flow at period t ,

i = risk-adjusted discount rate, and

rv = cash flows and value from the post-forecast period (residual value).

According to Rappaport (1994), the three main drivers that influence shareholder value are (1) time and height of cash flows, (2) reduction of risk of the cash flows, and (3) the residual value of the business, i.e., the value of the investment after

the forecast period. In general, a company should make an investment if its NPV is positive (Brealey and Myers, 2006) – or stated differently: if the incoming cash flows earn a return on investment at least equal to the risk-adjusted discount rate. This is not without implications for marketing. Traditionally, marketing metrics, such as sales growth and market share, focus on the success in the marketplace. However, as companies adopt the value based planning approach, for the evaluation of marketing actions, the impact on the economic value of the firm needs to take precedence over these traditional short-run metrics. Some scholars even argue that only if marketing adapts the familiar language of cash flows and capital structures it will experience greater appreciation and (re)gain a persuasive influence the strategy dialogue and in the negotiation for resources with top management (P. F. Anderson, 1982; Day and Fahey, 1988; Srivastava et al., 1998). Day and Fahey (1988, p. 46), who were among the first to discuss Rappaport's discounted cash-flow approach in the marketing literature, note in this context:

"Marketers can now expect that proposals for promotion campaigns, price changes, salesforce increases, and product line additions and deletions will increasingly be subjected to this new performance yardstick."

The most compelling argument for a value approach in marketing is that its forward looking nature recognizes the investive component of customer relationships. From this perspective, marketing expenditure that is traditionally viewed as short-term expenses, becomes an investment in a crucial intangible asset that creates future cash flows for the firm and, hence, value for its shareholders (Day and Fahey, 1988; Doyle, 2001; Hogan, Lemon, et al., 2002; Srivastava et al., 1998). Intangible assets—such as brand names, customer relationships and patents—are by definition hard to grasp and, due to the lack of objective measurability, often not included by accountants in their balance sheets. Yet in modern companies, tangible assets constitute only 20% - 30% of the market value of a firm (Capraro and Srivastava, 1997; Hogan, D. R. Lehmann, et al., 2002; Lev, 2001).

This discrepancy between market and book value shows, that while accountants typically do not consider intangible assets, investors do (Doyle, 2001). Hogan et al. (2002) even argue that a firm's customer relationships are 'super-assets' at the forefront of an implicit hierarchy among a firm's assets. Because a company's cash

flow comes from attracting, maintaining, and growing customers, other tangible and intangible assets are valuable only to the extent to which they can be deployed to increase this customer value. This view on customer relationships is a fundamental insight, because it brings the at first sight independent and possibly even conflicting goals of CRM (creation of value or utility for customers) and the shareholder value planning approach (long term profitability for the firm) into congruence.

According to Srivastava et al. (1998), investments in customer relationships result in increased market performance which in turn ultimately drives shareholder value by influencing its above mentioned three main drivers as depicted in Figure 7: Strong customer relationships (1) accelerate and increase cash flows due to increased purchase and referral behavior and responsiveness to marketing activities; (2) reduce the volatility and vulnerability of cash flows as a result of increased customer satisfaction, loyalty and lower defection risk; and (3) often have a substantial residual value, since customer relationships often outlast the forecast period and also contribute to additional cash flows (e.g., by cross-selling and word-of-mouth marketing.) Understanding that and how investments in customer relationships impact the firm value is not just of relevance as theoretical foundation for a financial valuation but also for marketing managers on an operational level. By analyzing the lifetime behavior of their customer base with respect to these drivers, they can understand what is happening to the value of their customer base in response to their marketing actions (Doyle, 2001).

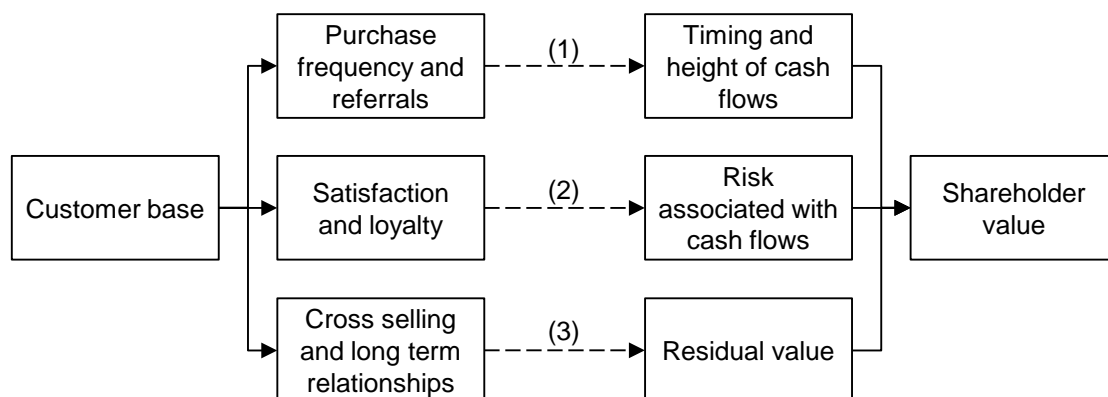


Figure 7: Impact of Customer Base on Value Drivers of Shareholder Value
Source: Own Illustration

From the value perspective on customer relationships derives also the exigency for a basic efficiency principle: investments in customer relationships must return their earning. Though already Jackson noted in 1985 that not all customers are financially attractive, relationship marketing has often been misinterpreted as the aim for "zero defections" (Reichheld and Sasser, 1990, p. 105). However, relationship marketing is costly and it might not pay to maintain relationships with all customers (Berger and Nasr, 1998), since customers with low switching costs and short time-horizons might not be financially attractive to the firm (Jackson, 1985). Hence, it is the goal of a value-based customer relationship marketing to focus on and seek strong relational bonds with the firm's *valuable* customers. While this ultimately can lead to the elimination of relationships with unprofitable customers, firing customers or refusing to serve them is seldom necessary. Instead, firms should design their value proposition or marketing campaign to attract profitable customers and be unappealing to less desirable customers (Bolton and Tarasi, 2006).

Therefore, it is crucial for a firm to be able to precisely measure the profitability and value of its market-based assets. In the context of CRM, customer lifetime value and customer equity have become the standard metrics for this purpose. In the next chapter I will discuss these in detail.

2.3.2 Quantification of Customer Relationship Value

The economic value of a customer is usually formalized as the *customer lifetime value* (CLV) which is "the present value of all future profits obtained from a customer over his or her life of relationship with a firm" (S. Gupta et al., 2006, p. 141). The similarity in definition of CLV to NPV is also reflected in its mathematical formula which follows the DCF approach¹⁰:

$$CLV = -AC + \sum_{t=0}^n \frac{C_t}{(1+i)^t} \quad (2.2)$$

where

t = period index,

¹⁰ Customer indices are omitted for better readability, here and in the following.

- n = duration of customer's relationship with the firm,
 AC = initial customer acquisition cost,
 C_t = contribution margin at period t , and
 i = risk-adjusted discount rate.

In most cases the actual lifetime of the customer with the firm is of course not known ex ante. In this situation some researchers use an arbitrary time horizon of e.g. three years (Rust et al., 2004). Others calculate an expected lifetime duration based on the churn rate as $n = 1/churn$ (Reinartz and V. Kumar, 2000a). The use of an expected lifetime has, however, been shown to generally overestimate the actual CLV because it does not correctly reflect the time value of customer revenues (S. Gupta and D. R. Lehmann, 2003). Therefore most formulations calculate CLV by explicitly incorporating the possibility that the customer switches or defects in any period.

There are two broad classes of models for customer retention: *always-a-share* models assume that customers freely switch between and temporarily discontinue their purchases with vendors, whereas under the *lost-for-good* assumption, customers are either fully committed to the vendor or completely lost (Berger and Nasr, 1998; Jackson, 1985). Determining the CLV in the first case typically involves complex migration models, for example using Markov-chains (Donkers et al., 2003). Therefore in practice, CLV is usually calculated assuming the latter case by using a retention model and treating returning customers as new ones (S. Gupta et al., 2006). Retention models account for the possible customer defection by including a retention probability in the calculation of the CLV. If r_j is the probability of customer retention in period j , then the probability that a customer is still active in period t is $\prod_{j=1}^t r_j$. Hence, equation (2.2) can be rewritten as a retention model as

$$CLV = -AC + \sum_{t=0}^{\infty} \frac{C_t \cdot \prod_{j=1}^t r_j}{(1+i)^t} \quad (2.3)$$

where

- t, AC, C_t, i have the same meaning as in equation (2.2), and
 r_j = retention rate in period j .

Obviously, just as the customer lifetime is typically unknown ex ante, in most situations it is hard to predict future contribution margins and retention rates¹¹. Therefore, in practice contribution margins and retention rates are often assumed to be constant. Under this assumption, equation (2.3) simplifies to the following expression (S. Gupta et al., 2006; S. Gupta and D. R. Lehmann, 2003):

$$CLV = -AC + \sum_{t=0}^{\infty} \frac{C \cdot r^t}{(1+i)^t} = -AC + \frac{C \cdot r}{(1+i-r)} \quad (2.4)$$

where

t, AC, i have the same meaning as in equation (2.2),

C = (constant) contribution margin per period, and

r = (constant) retention rate.

To ensure accuracy and actionability, Bolton and Tarasi (2006) recommended to determine the estimates of these parameters at the individual customer or customer segment level. While this micromarketing is useful from an operational perspective (e.g., to determine the individual level marketing efforts) strategic decisions require a customer value perspective on an aggregated level (Blattberg and Deighton, 1996; Bolton and Tarasi, 2006). For this purpose, many researchers focus on *customer equity* (CE), which is defined as the lifetime values summed over all current and potential future customers (Blattberg et al., 2001; S. Gupta et al., 2004; Rust et al., 2004):

$$CE = \sum_{i=1}^n CLV_i^{current} + \sum_{j=1}^m CLV_j^{potential} \quad (2.5)$$

where

i, j = customer index,

n = number of current customers,

m = number of potential customers

$CLV_i^{current}$ = CLV of current customer i , and

$CLV_j^{potential}$ = CLV of potential customer j .

¹¹ However, some researchers have used trends or individual specific margins and retention rates (Borle et al., 2008; v. Wangenheim and Lentz, 2005).

Consequently, CE realizes the above elaborated basic premise of the value based planning approach. In fact, the great importance of the 'super-asset' customer relationship is further highlighted by findings of Gupta et al. (2004) who show that the CE of a firm can serve as a good proxy for the actual market-based value. This also implies that strategies to improve the CE (i.e., to improve customer acquisition, retention, and margins) will also enhance the firms market or shareholder value (S. Gupta and Zeithaml, 2006; Rust et al., 2004). Blattberg and Deighton (1996) show for example how—in the light of scarce marketing resources—CE-impact can serve as the criterion to balance spending on customer acquisition and retention, giving rise to a new approach to marketing: customer equity management—"a comprehensive management approach that focuses the efforts of the firm on increasing the lifetime value of individual customers [...] in a way that maximizes customer equity" (Hogan, Lemon, et al., 2002, p. 5).

2.4 Theoretical Aspects of CRM

2.4.1 Reflections on the Fundamental Axiom of CRM

From what has been discussed, the motivation for firms to engage in relationship marketing is apparent: it can be lead back either to superior economics of customer retention (Reichheld and Sasser, 1990; Reichheld and Teal, 1996; Rosenberg and Czepiel, 1984) or the competitive advantage that customer-firm relationships provide (Bolton and Tarasi, 2006, p. 9; Ganesan, 1994; McKenna, 1991; Woodruff, 1997). However, a relationship and its advantages for the firm can develop only if its customers are likewise willing to engage in relationship patronage. The therein connoted ongoing and cooperative market behavior of firms and consumers (Gummesson, 1996; Parvatiyar and Sheth, 2001; Sheth and Parvatiyar, 1995b) requires a commitment from customers that, at least from a classical microeconomic perspective, is unfavorable. Relational market behavior of consumers constitutes a purposeful reduction of choice, where they are forgoing the opportunity to choose another vendor, product, or service in favor of their loyalty. Or, in other words: many of a firm's benefits of relationship marketing redound to the customers' disadvantage. Sheth and Parvatiyar (1995a,

p. 256) note in this context that "[t]he fundamental axiom of relationship marketing is, or should be, that consumers like to reduce choices by engaging in an ongoing loyalty relationship with marketers". And indeed, based on practical experience and several studies on customer loyalty, it is known that at least some customers actually do so and engage in customer-firm relationships, voluntarily undergoing such confinement. Yet, the implicitly premised motivation to engage in these relationships is from the customer perspective by no means self-evident.

The explication lies in relational benefits, i.e., additional benefits that customers receive in addition to the core service or good as a result of cultivating a relationship. In a landmark study, Gwinner, Gremler, and Bitner (1998) found that customers experience primarily three types of benefits: confidence benefits, social benefits, and special treatments benefits. Confidence benefits are mainly of psychological nature and arise from feelings of reduced anxiety, trust, and reliance. Social benefits are mostly due to interpersonal contact. They describe benefits received from fraternization and personal recognition. And lastly, special treatment benefits are mainly economic considerations and relate to discounts, munificence, time savings, or preferential treatments. While Gwinner et al.'s label 'relational benefits' has a univocally positive connotation, Bendapudi and Berry (1997) also point out that the customers' receptivity for relationships depends both on dedication (i.e., that they want to stay in the relationship primarily due to trust in the partner) and on constraints (i.e., that they have to stay in the relationship primarily due to dependence on the partner). Both sets of motivations are important, but influence the relationship in different manners. Whereas constraints only determine the stability of the relationship, dedication primarily determines whether a relationship will grow.

Obviously one would assume different qualities of customer loyalty in constraint- and dedication-based relationships. While much of research and managerial interest is directed towards behavioral loyalty referring to the actual purchase behavior, "there is more to brand loyalty than just consistent buying of the same brand" (Day, 1969, p. 29). That is because "this type of loyalty only captures the static outcome of a dynamic process" (Jacoby and Chestnut, 1978, p. 43). But retention is not loyalty. Instead, loyalty consists not only in repeated purchases but also in a strong internal disposition (Day, 1969). Oftentimes 'true loyalty' is

ascribed to this affective dimension rather than repeated purchases merely due to situational factors. What distinguishes the two forms of loyalty is commitment and trust in the former and inertia in the latter case (Olson and Jacoby, 1971).

In fact, the social constructs of commitment and trust have even been shown to be key for successful customer relationships (Morgan and Hunt, 1994). Combining these two dimensions, Dick and Basu (1994) proposed an integrated framework that differentiates customer loyalty with respect to relative attitude compared to alternatives and amount of repeat patronage as depicted in Figure 8.

		Repeat Patronage	
		Low	High
Relative Attitude	Low	<i>No loyalty</i>	<i>Spurious loyalty</i>
	High	<i>Latent loyalty</i>	<i>Loyalty</i>

Figure 8: Four Types of Customer Loyalty
Source: Dick and Basu (1994)

The thorough understanding of mechanisms underlying customers' motivations for a loyal relationship engagement of consumers is crucial for an effective relationship marketing (Iacobucci and Hibbard, 1999; Sheth and Parvatiyar, 1995a). In this regard, several authors have criticized the current understanding as "theoryless [...] stack of fragmented philosophies" (Gummesson, 1997, p. 267), "blind spot" (Fernandes and Proença, 2008, p. 153) or rhetoric and detached from reality (Fournier et al., 1998; O'Malley and Tynan, 2000). Therefore, I will introduce and discuss the most important theories in the subsequent sections. Reflecting the diverse genealogy of relationship marketing, consumers' motivations for loyal relationship engagement have been analyzed using several theories. Especially in consumer service markets, economic mechanisms can only partly explain the observed, since individual behavior is typically strongly

influenced by psychological and sociological factors (Alderson, 1952; Morgan and Hunt, 1994). Therefore after discussing two basic economic theories, I follow Sheth and Parvatiyar (1995a) and take a psychological and sociological perspective discussing several explanations based on theories of learning, perceived risk, and cognitive consistency.

2.4.2 Transaction Cost Theory

While from a neoclassical perspective exchanges are assumed to be frictionless, i.e., to occur instantaneous and without cost, transaction cost theory acknowledges that the transfer of a good or service across a technologically separable interface indeed involves effort. Moreover it provides a framework to study the effectiveness of governance structures (Coase, 1937; Williamson, 1975, 1979, 1981). It breaks, inter alia, with the hyperrationality of the economic man and acknowledges "human nature as we know it" (Knight, 1965, p. 270) by making two fundamental behavioral assumptions: bounded rationality and opportunistic behavior of human agents. As a result, exchanges are subject to incomplete contracting. Furthermore the coordination thereof is associated with *transaction cost* that are sought to be minimized. Transaction costs consist of cost of initiating, maintaining, controlling, and terminating the relationship as well as opportunity cost. According to Williamson (1979), the critical dimensions leading to a disproportionate increase of these transaction cost are (1) uncertainty, (2) frequency of transactions, and (3) the level of relational-specific investments. Ideally, exchange parties choose the governance structure that minimizes the associated transaction cost. In the context of relationship marketing the two relevant governance structures are market-based coordination and relational cooperation (Ring and van de Ven, 1992).

Uncertainty refers to unexpected outcomes and asymmetry of information. Sources of uncertainty can be external, caused by market dynamism such as the variability in product availability and prices. Or they can also be internal, caused by task ambiguity making it difficult for the customer to ascertaining the quality of the offering. Therefore, a higher level of uncertainty generally implies higher transaction cost because a consumer will have to spend more time and effort in

searching for product or vendor information and monitoring the process and outcome.

A greater frequency at which transactions reoccur in general implies increased transaction costs if each transaction is handled separately. In contrast, exchange parties in a relational setting could anticipate lower transaction costs as the costs associated with negotiating, monitoring and enforcing performance can be recovered with multiple recurring exchanges (Bendapudi and Berry, 1997). In addition, the firm's expectation of repeat business with the same customer should discourage opportunism and consequently reduce the customer's cost to safeguard against it (Williamson, 1975).

According to Williamson (1985), the most important dimension for describing transactions is the relationship-specificity of investments. While in an inter-firm context these are often tangible and can be quite substantial (such as investments in machinery and common interfaces), in consumer markets these are mainly intangible and consist mostly in relationship-specific know-how. More important for customers may hence be opportunity cost. By engaging in relational market behavior, a customer limits his choice which potentially increases his "opportunity cost of foregone exchange with alternative partners" (Dwyer et al., 1987, p. 14). Increased vendor dependence also increases the customer's exposure to idiosyncratic vendor problems, such as e.g., supply difficulties, that the customer has to absorb (Jackson, 1985).

Transaction cost economics is a standard framework to analyze buyer-seller relationships. Its normative emphasis is well-supported in empirical research (Mudambi and Mudambit, 1995; Shelanski and P. G. Klein, 1995). In particular, research on inter-firm relationships supports the premise that relationships among exchange partners support relational-specific investments while reducing transaction costs and safeguarding from opportunistic behavior (Heide and John, 1990; John, 1984; Wathne and Heide, 2000). Cannon and Perreault (1999, p. 454, p. 456) caution however that "we should not assume that the most closely coupled buyer-seller relationships are necessarily the most satisfying ones" and "if relationships meet customer needs, they are likely to endure, no matter how closely connected".

2.4.3 Principal-Agent Theory

The principal-agent theory offers a model for the explanation and optimal organization of socio-economic relationships where one party—the *principal*—depends on the other party—the *agent*—to carry out some action on his behalf (Bergen et al., 1992; Jensen and Meckling, 1976). Assuming an opportunistic and self-interest nature of the agent, it deals with difficulties due to uncertainty and information asymmetry that arise in these cooperations¹². In customer relationships, the customer as the party typically with greater dependence is in general designated the principal who monitors and judges the seller as his agent.

The principal-agent theory describes three types of information asymmetries—*hidden characteristics*, *hidden actions* and *hidden intentions*—that the agent can exploit to the disadvantage of the principal. Hidden characteristics refer to the principal's inability to ascertain particular characteristics of an agent and respective attributes of the desired output. Especially for complex outputs (i.e., customized services) customers are seldom able to judge the quality ex ante due to a high proportion of inherent credence and experience qualities (Bruhn, 2002, p. 25). Consequently, they might choose a disadvantageous agent (*adverse selection*). Once the relationship is established, the agent can exploit the fact that the principal cannot monitor whether the agent behaves in accordance to the agreed because of cognitive, time, or cost constraints (*moral hazard*). This is the case for example in complex services where suppliers could degrade quality levels such as confidentiality or security levels. Finally, the agent can exploit the principal's dependence if he has intentions that are divergent to the principal's goals (*hold-up*).

From the principal's (i.e., the customer's) perspective, these conditions encourage relational engagement by equalization of the information asymmetry and providing incentive and risk sharing structures. First, over the course of the relationship, the principal becomes more knowledgeable about the agent and his offering, hence equalizing the information asymmetry (Bruhn, 2002, p. 26). Moreover, screening cost to assess the hidden characteristics of a supplier can be

¹² It is to note, however, that the validity of assumptions and expressiveness of the principal-agent theory is not undisputed (Eisenhardt, 1989; Mirrlees, 1999; Waterman and K. J. Meier, 1998)

recovered over a multitude of transactions (compare section 2.4.2). Second, the agent's expectance of recurring transactions should prevent the agent from exploiting these information asymmetries in the first place (N. Kumar et al., 1995). Similarly, market mechanisms (such as price premiums which the principal can withdraw if he suspects opportunistic behavior) provide a similar incentive mechanism (B. Klein and Leffler, 1981). And finally, borrowing from sociology, the embedding of transactions in (social) relationships provides a regulation mechanism by social norms such as trust, honesty, and fairness (Granovetter, 1985; S. P. Shapiro, 1987).

2.4.4 Learning Theory

Learning is one of the major determinants of human behavior. It can broadly be defined as "the process by which experience leads to changes in knowledge or behavior" (Blackwell et al., 2006, p. 88). This process has been a central research topic over the last 100 years. Many different views and theories have been proposed, the most relevant in the context of relational market behavior being behavioral and cognitive learning theories. Each of these describes different concepts and mechanisms of learning that affect relational market behavior.

Behavioral learning theory is probably the earliest formulation of a coherent theory of learning. It defines learning in terms of observable changes in behavior and as a result of actual lived experience (Blackwell et al., 2006, p. 88). The fundamental concept of behavioral learning theories such as classical (Pavlov, 1927) or operand conditioning (Skinner, 1938) is stimulus-response-associations that represent a functional relationship between environmental cues or ideas and behavior.

From this behavioral perspective, relational market behavior can be explained with the fundamental observation that positively reinforced behavior is more likely to reoccur than non-reinforced behavior (Thorndike, 1905, p. 166). Accordingly, to the degree that past purchase decisions were positively reinforced through for example satisfactory consumption experiences, customers are likely to engage in repeated patronage. Furthermore, loyal market behavior can also be self-enhancing because efficiency gains that consumers experience from

increasing habitualization of the purchase process lead to additional positive reinforcement. This conditioning also creates consumer inertia, i.e., the consumers' unwillingness to switch to other choices (Sheth and Parvatiyar, 1995a). From an economic perspective, this inertia can be explained with switching cost due to these efficiency gains. This is because to the extent that the task performance efficiency gains are vendor-specific, they also make switching to another vendor—for which similar efficiency gains have not been made—costly to the consumer. Johnson, Bellman, and Lohse (2003) label this phenomenon by the term *cognitive lock-in*. Murray and Häubel (2007) show however in their empirical study that this effect is fully mediated by the steepness of the consumer's learning curve in the relationship. That means this effect is expected to be less pronounced for product classes of high perceived ease of use.

While behaviorists consider the individual's mind as a black box, cognitive learning theories are concerned with the processes which occur inside the brain and nervous system as a person learns. From this perspective, changes in an individual's knowledge are thought to be internal and unobservable phenomena due to active mental or cognitive processes. Behavior is seen merely as a glimpse at these underlying changes. Consequently, these theories explicitly assume learning to be the result of a solely cognitive effort such as the acquisition and encoding of new information and its integration with existing beliefs—possibly even devoid of any personal experience. In essence, the two levels on which cognitive learning occurs are (1) rote memorization, i.e., repeated exposure to information, and (2) problem solving, i.e., the active processing of information to reach a certain judgment (Sheth et al., 1999, p. 311).

This cognitive school regards consumers as having to solve purchasing problems (e.g., what and where to buy and how much to pay). Learning consists in a simplification of this decision process based on previous knowledge. Given the proliferation of choices that consumers are confronted with, learning leads to limiting the number of vendors and products under consideration to an *evoked set* when contemplating purchasing a unit of the product class (Howard and Sheth, 1969; Reilly and Parkinson, 1985, p. 98). Repeat purchase behavior then is a situation of routine problem solving where the evoked set serves as decision heuristic to become more efficient.

Although consumers in general seek routinization of the choice process, they also seek variety when they feel bored (Howard and Sheth, 1969). It has been shown that consumer purchase behavior follows a cyclical pattern from routinization to variety seeking (McAlister and Pessemier, 1982; Raju, 1980). As depicted in Figure 9, when consumers arrive at a certain level of familiarization they start to review their available alternatives to offset their boredom and possibly churn to a different provider.

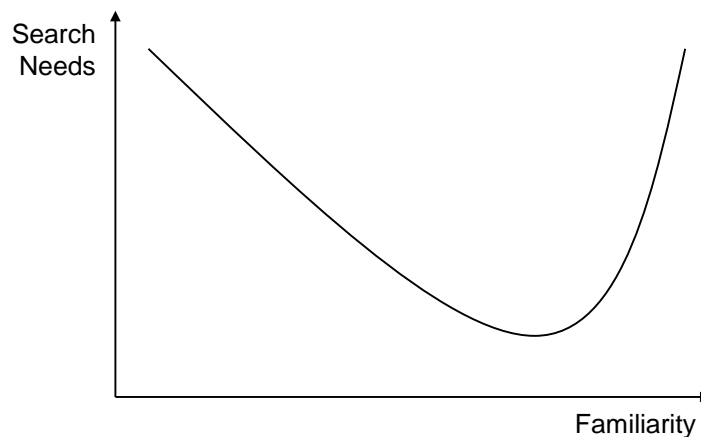


Figure 9: Familiarity Curve
Source: Howard (1989, p. 101)

2.4.5 Risk Theory

Another key motivation of consumer behavior is to reduce risk (Bauer, 1960). In general, any choice confronts individuals with risk, since the outcome and the consequences thereof can only be known in the future. The focal construct is the consumer's perceived risk. This is the subjective judgment of the risk in terms of the magnitude of the consequences, and the probabilities that these consequences occur (Dowling and Staelin, 1994). Perception of risk is painful for consumers and often produces feelings of psychological discomfort or anxiety (J. W. Taylor, 1974). In an effort to avoid these unpleasant feelings, individuals use a variety of methods to relieve the perceived risk such as (1) buy from brands that the customer has had satisfying experiences; (2) buy products carried by a store that is considered dependable; (3) rely on reputation of major brands; (4) shop around and compare features of the product; (5) ask family and friends for advice; (6) buy tested and approved products; (7) rely on endorsement by trusted sources and

word-of-mouth; (8) buy the most expensive and elaborate model; and (9) buy the product that offers money-back-guarantee (Roselius, 1971).

Interesting in the context of relationship marketing is that these risk-reducing strategies have opposing effect with regard to relational market behavior. For one, confidence benefits from repeat patronage seem to be the most highly rated risk reliever (Gwinner et al., 1998; Roselius, 1971). Consequently, the higher the perceived risk in a purchase decision, the greater is the motivation for consumers to engage in relational market behavior (Sheth and Parvatiyar, 1995a). Accordingly it has been shown that if consumers have the opportunity to rely on a brand name they previously had positive experiences with, the more they tend to buy that brand repetitively without engaging in much pre-decision information seeking (Sheth and M. Venkatesan, 1968). On the other side, with relational engagement exists also the risk of a lock-in, both in a cognitive (see section 2.4.4) and an economic (see section 2.4.3) sense. The anticipation of this risk by the consumer can however also have a negative effect on relationship formation (Bruhn, 2002, p. 152).

Second, consumers also engage in external search for information in order to develop greater ability to evaluate their choices. In particular, this search is directed towards collecting information about other available brands and can ultimately result in their inclusion in the evoked set (Dowling and Staelin, 1994). This would imply a more transactions oriented buying behavior based on subjectively well informed decisions. Active information seeking seems to be important mainly initially and as a strategy to alleviate the risk of feeling foolish if the product eventually turns out unsatisfactory (Roselius, 1971).

And lastly, standardization and extrinsic cues such as service guarantees or quality certificates reduce the perceived risk in the first place and, thus, encourage a transactional buying behavior (Shimp and Bearden, 1982). Similarly, with increasing expertise, consumers are more confident in their ability to accurately judge products and, thus, the perceived risk typically decreases (Agrawal, 1995; Hisrich et al., 1972). Therefore, over time one would also expect the customer to feel more comfortable with exercising his alternative choices, which acts oppositional on the establishing brand loyalty.

2.4.6 Cognitive Consistency Theories

Consumers' engagement in relational buying behavior can also be explained with cognitive consistency theories, which suggest that individuals strive to maintain a psychological harmony in their cognitions and behaviors (Sternberg, 1987). Inconsistencies or dissonances in this system create psychological tension, which individuals are presumed to avoid. A popular example of these theories is cognitive dissonance theory which focuses on the mechanisms used when conflicts arise (Festinger, 1957). One source of dissonance is post-decision dissonance, i.e., the observation that after an individual has made a decision, he will feel dissonance regarding the possibility of it being wrong. In this situation, Festinger (1957, p. 3) describes that in general consumers rationalize their choices ex post by enhancing positive and suppressing negative aspects of the chosen alternative; and in reverse, by enhancing the negative and suppressing the positive aspects of a rejected alternative.

Research in psychology and consumer behavior describes several concrete occurrences of this basic dissonance reduction strategy. Among those are most notably *attitude changes* and *selective exposure*. Attitude change describes the observation that after consumers have made a choice, they rate the chosen alternative higher and the alternatives lower (Hunt, 1970). Selective exposure denotes that consumers seek new information confirming the decision and avoid or even neglect new information that disconfirms the decision (Frey, 1986).

From this perspective, a consumer's purchase represents his decision that he strives to justify as the correct one. The reduction of post-choice dissonance should lead him to increase his preference for the brand (attitude change) and, furthermore, avoid positive information about rival brands (selective exposure). This, again, increases the probability of repeat purchase (Mittelstaedt, 1969). Interestingly, according to cognitive dissonance theory, constraint-based motivations can lead to dedication. A consumer who is dependent on his exchange party may try to justify this dependence by professing dedication to the relationship and, hence, portraying the relationship to himself in a more positive light (Bobocel et al., 1994).

Yet, it has been shown, that cognitive dissonance effects apply only for high involvement product classes (Korgaonkar and Moschis, 1982). For products of low

involvement, the effect can be even oppositional. Several studies in the latter context show that discrepancies between expectations and actual performance are not assimilated by the consumer congruent with his expectations but rather magnified (Sherif and Hovland, 1961)¹³.

2.4.7 Social Exchange Theory

Social exchange theory is rooted in economics, psychology and sociology. It was first formulated by Homans (1958) to explain social behavior in a social exchange relationship. It differs from an economic exchange (compare section 2.2.1) in the unit of analysis and in particular with regard to the assumed interaction mechanism between the actors. While social exchange theory considers the relationship between actors, economic exchange theory assumes actors to interact not with each other but with a market. The fundamental posit of social exchange theory is that individuals ultimately strive for balance in a constant and subjective evaluation of the relationship's cost and benefits. Or, as Emerson (1976, p. 335) puts it: "the economic analysis of noneconomic social situations", thereby emphasizing that the valuta is not necessarily of a monetary form. Inter alia, benefits can include social status, recognition, and emotional comforts. Costs additionally comprise sacrifices of time or lost opportunities.

In a widely cited quote, Homans (1958, p. 606) summarized the essence of the theory:

"Social behavior is an exchange of goods, material goods but also non-material ones, such as the symbols of approval or prestige. Persons that give much to others try to get much from them, and persons that get much from others are under pressure to give much to them. This process of influence tends to work out at equilibrium to a balance in the exchanges. For a person in an exchange, what he gives may be a cost to him, just as what he gets may be a reward, and his behavior changes less as the difference of the two, profit, tends to a maximum."

¹³ Strictly speaking this observation does not come from cognitive consistency but contrast theory.

This reciprocity is an important concept for the stability of a relationship. When a person does anything beneficial for another, there is the expectation that the other will reciprocate to rebalance the relationship. Likewise, also the beneficencee will feel obligation. In the context of relationship marketing, research often focuses on relationship specific investments, which according to social exchange theory is expected to induce substantial reciprocatory actions by customers. This notion is in general supported by empirical research though the implied link is found to be comparably weak (Palmatier et al., 2006; Pervan and L. W. Johnson, 2003). Interestingly, individuals pay more attention to negatives than to positives in the relationship. Therefore, an unfulfilled expectation of reciprocation of a relational engagement on behalf of the consumer might lead to the cessation of his relational market behavior (Palmatier et al., 2006).

On the other hand, a relational engagement of the seller does not automatically induce relational engagement by the customer by means of reciprocation. The reciprocity obligations created by this engagement can cause feelings of personal discomfort until they are repaid. Since this constitutes a form of cost for the consumer, some consumers even react with avoidance of sellers with high relationship orientation (Cialdini, 1988).

The continuance of a relationship is not just simply a matter of how rewarding it is for the participating actors, but also related to the expectations of other alternatives—or in turn: the lack thereof. This comparison leads directly to another important concept of social exchange theory: dependence and the resulting power structures in a relationship, which derive from the fact that some actors control more highly valued resources than others (Emerson, 1962). Generally, research in relationship marketing confirms this role of power-dependence structures in customer-firm relationships (Andaleeb, 1996; Bendapudi and Berry, 1997). However, it is also pointed out that a mutual dependence has the greatest performance enhancing impact on a relationship and that asymmetric dependence can generate conflicts and undermine cooperation (Gassenheimer et al., 1998; Hibbard, N. Kumar, et al., 2001).

2.4.8 Synthesis

Though much work has been done analyzing and highlighting the relational benefits for organizations, research on the consumer's motivation to engage in relational market behavior is still scarce (Bendapudi and Berry, 1997). Because indisputably this perspective is fundamental to understanding mechanisms and dynamics of customer relationships in a consumer context (Sheth and Parvatiyar, 1995a), I discussed relevant economic and behavioral theories applying them to analyze this perspective. Their key insights with respect to relationship versus transactions orientation are summarized in Table 2.

Table 2: Summary of Theoretical Contributions to Customer Engagement in Relationships

Theoretical Approach	Arguments for relational market behavior	Arguments for transactions-oriented market behavior
Transaction Cost Theory	- Reduced cost of negotiating and monitoring	- Opportunity cost of foregone exchange with alternative partners - Dependence on provider-specific problems
Principal-Agent-Theory	- Equalization of information asymmetries - Incentive against opportunistic behavior	
Learning Theory	- Positive reinforcement induce habitualization of buying - Efficiency gains due to learnt behavior represent lock-in	- Variety seeking
Risk Theory	- Familiarity reduces perceived risk	- Information seeking as risk reliever - Over time, increasing confidence to exercise alternative choices - Anticipation of lock-in risk
Cognitive Consistency Theory	- Reduced psychological tension for high-involvement products	- Greater susceptibility of underperformance for low-involvement products
Social Exchange Theory	- Reciprocation of relational benefits	- Attractiveness of alternatives affects strength of relationship - Cessation of relationship if relational engagement not reciprocated - Reciprocity obligations possibly discomfoting

Interestingly, only few theories provide univocal arguments for either relationship or transactions orientation. Especially in consumer markets this leads to the observation that "exchange in consumer markets is likely to be characterized by both transactional and relational elements" (O'Malley and Tynan, 2000, p. 806). The degree and the concrete direction to which they take effect vary with contextual factors such as product-market attributes and customer and seller characteristics (Arndt, 1979; Christy et al., 1996; Dwyer et al., 1987; Fernandes and Proença, 2008; Gruen, 1995; Pressey and Mathews, 2000). Consequently, product-markets, customers, and providers should differ with regard to relationship potential as depicted in Figure 10.

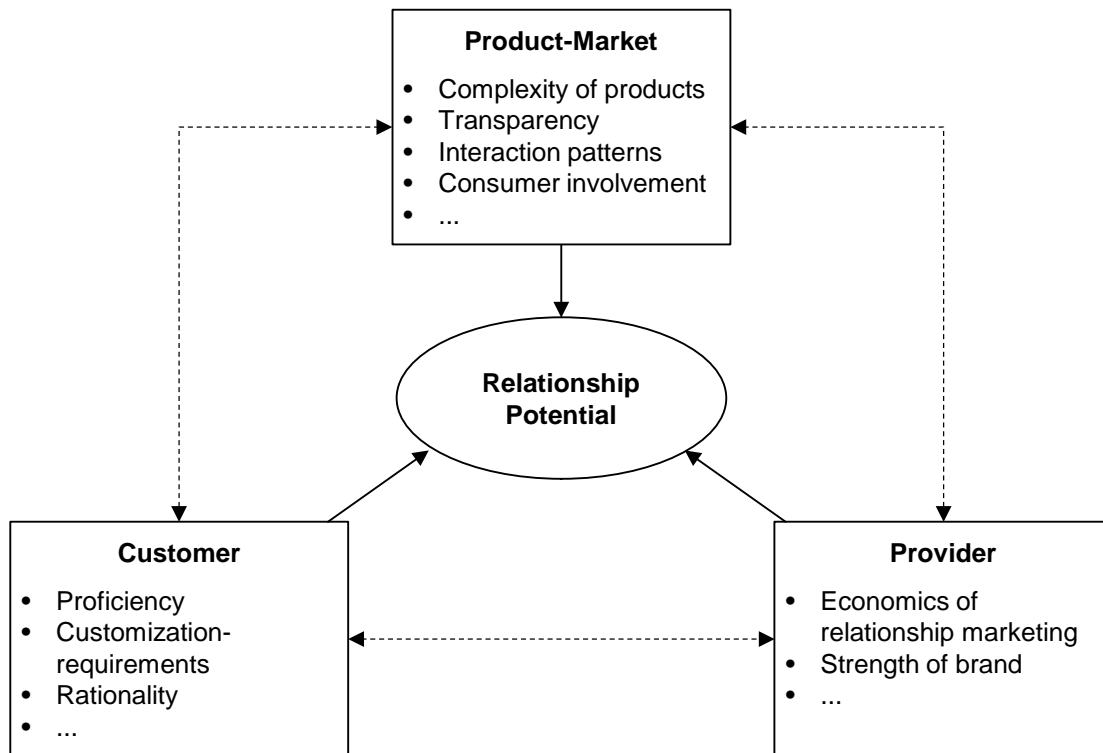


Figure 10: Influence of Product-Market, Customer, and Provider Characteristics on Relationship Potential
Source: Own Illustration

Not all product-markets are equally suited for customer-firm relationships. Based on the discussion of relevant theories the important attributes include heterogeneity, complexity, and the degree of credence and experience qualities of products (Cheng and A.-H. Lee, 2011; Christy et al., 1996; Fernandes and Proença,

2008); transparency, cooperation, and competition in the market (Hunt and Morgan, 1994); the integration, frequency, and directness of interaction (Jackson, 1985, p. 122); and whether the context is of high involvement (Pressey and Mathews, 2000).

Similar considerations apply also for customer characteristics, albeit they are often interrelated with product and market specifics. Not all customers wish to engage in relationships (Bendapudi and Berry, 1997; Fournier et al., 1998). For example, a customer with high uncertainty about a product field, perceived need for training, and higher-than-normal customization-requirement or quite simply lower rationality in his decision processes might show a higher relationship orientation (Christy et al., 1996; Egan, 2001).

And, finally, also characteristics of the seller influence the formation of relationships. Relationship marketing is costly. If customer acquisition cost are low and each individual customer only represents a small share of the seller's business, the cost of maintaining the relationship might exceed it (Egan, 2001). And if relationships are implicit and for instance based on repeat purchases, the strength of the provider's brand is an important facilitator (Dowling and Uncles, 1997; Roselius, 1971).

The relationship potential also seems to vary over time. In the context of the preceding discussion this can be led back to the fact that characteristics of the product-market, customers, and sellers—or at least the perception thereof—change over time (Bruhn, 2002, p. 22). Based on basic intuition and research findings one would for example expect that as consumers become more knowledgeable and experienced, their information disadvantage to the seller should diminish and, hence, they should feel more confident in their abilities leading to a decrease in perceived risk (Grayson and Ambler, 1999; Parasuraman, 1997).

This observation highlights the importance of time-related aspects in customer relationships. In line with the paradigm shift that relationship marketing constitutes, a theoretic exploration must also change from a static to a dynamic perspective. The next section is dedicated to this.

2.5 Development of Customer-Firm Relationships

2.5.1 Exigency and Status-Quo of the Dynamic Perspective

Customer relationships are dynamic in nature (Ganesan, 1994; Parasuraman, 1997). Like any relationship, they change, evolve, and either strengthen or weaken with the passing of time. While much conceptual work has been done with regard to the link between shareholder value and customer lifetime value, far less attention has been given to modeling the dynamics of customer relationships (Netzer et al., 2008). This lack of research is even more astonishing considering that customer value and respective metrics are by definition forward-looking and become managerially relevant only in a prospective assessment. In their synthesis of a thought leadership conference on managing customers for value, Kumar Lemon, and Parasuraman (2006, p. 90, 91) highlight in their research agenda that "these models still implicitly assume that customers' behavior is relatively stable". In order to move from infancy to adulthood, they "need to include the notion that customers change over time".

So far, scholars have approached this topic from two angles¹⁴. For one, in existing work much emphasis has been placed describing the formation and development of relationships from an ideal-typical angle how it ought to be in a normative sense. While this kind of 'ought-proposition' which I will describe in the following section 2.5.2 is important, critics have argued that it is in fact an idealization of relationships which is mostly due to the great enthusiasm about relationship marketing and lacks concrete empirical evidence to substantiate it (S. W. Brown et al., 1994; S. Brown, 1998; Egan, 2001; O'Malley and Tynan, 2001). Against this background, I take a descriptive perspective in section 2.5.3 and discuss actual empirical evidence—i.e., the factual 'is-propositions'—in a meta-analysis of past empirical research findings.

¹⁴ See e.g., Morgenstern (1972) for a discussion of normative, descriptive and predictive approaches in economic theory.

2.5.2 Conceptual Contributions

Relationship marketing researchers generally assume relationships—just like customers and products—to operate according to a lifecycle process analogous to the elemental process of birth, growth, maturity, aging, and death. The basic premises of this assumption are, that (1) objects have finite lifetime and (2) that during their lifetime objects traverse these stage-dependent phases sequentially, where each phase is characterized by a set of specific properties that objects in this phase share. Understanding the point in lifecycle in which the object currently resides, can hence provide insights into how the object behaves, now and in the future.

The customer relationship lifecycle is inspired by the prominent and widespread product life cycle that emanated from the theory of diffusion and adoption of innovations (Bruhn, 2002, p. 42; Day, 1981). Just like the product life cycle describes the sales of a product, a product segment, or even an entire industry from the time it is first placed on the market until it is removed, the customer relationship life cycle models the ideal evolution of the association between the potential customer and the firm. Especially with the shift in marketing's orientation from transactions to relationships, this customer-centric perspective is gaining increasing importance as Tirey (1995, p. 31) summarizes in a persuasive and compelling argument:

"Terms such as acquisition, growth, and retention are inherently flawed because they do not present a customer view of the relationship, only the seller's view. Customers do not think about being acquired or being gawn. By adopting a lifetime perspective, knowing the customer, where they are in the relationship with the company, where they are falling out of the relationship – a company learns to think like a customer. All of this enables a company to identify the product, processes and communication requirements to maximize shareholder value, market share and satisfaction."

According to Dwyer, Schurr, and Oh (1987) the development of relationships passes through five stages: awareness, exploration, expansion, commitment, and dissolution as depicted in Figure 11. The authors originally described five sub-processes that support the traversal through the phases. However, today most

research conceptualizes this traversal to be mediated by the relational constructs of trust, commitment, relationship satisfaction, and/or relationship quality (Palmatier et al., 2006).

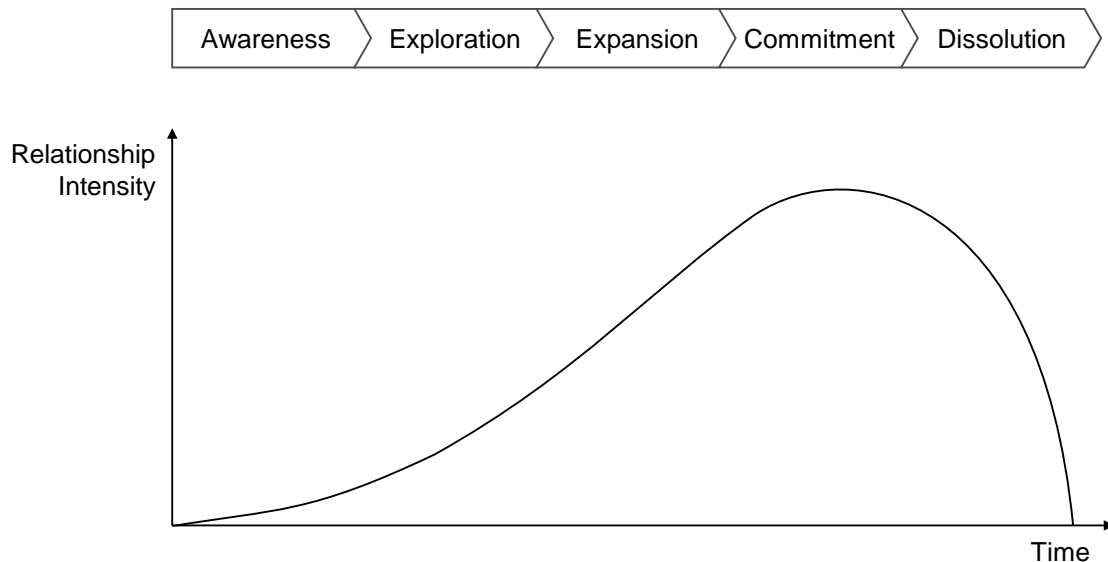


Figure 11: Customer Relationship Lifecycle
Source: Bruhn (2002, p. 46)

The awareness phase describes a party's recognition that the other party is a feasible exchange partner. Since this phase is devoid from any interaction, no sales but typically only marketing cost accrue for the vendor. Any type of interaction marks the beginning of the subsequent exploration phase. Exploration refers to a trial phase where first transactions are made. Both phases are rather instable due to limited confidence in the potential partner's abilities and willingness to explore the relationship. If the initial experiences are positive and superior to competitive offers, an intensification of the relationship takes place in the expansion phase. The rudiments of trust and joint satisfaction established in the preceding phase now lead to greater affective attachment and, hence, a continual increase in the interdependence of the exchange partners. In this phase revenues typically increase and cost for both parties decreases due to greater trust and a routinization of the process. In the commitment phase, loyalty is finally achieved and calculative trust is replaced with knowledge-based trust (Rousseau et al., 1998) leading to mutual unrecoverable investments. Low information and coordination effort leads to a broadening of the relationship and a further cost reduction. The dissolution phase finally marks the termination of the relationship.

Though dissolution is conceptually the last phase in the sequence, the possibility of withdrawal from the relationship is imminent throughout the whole process.

Relationship intensity can be defined in several constructs, among them being psychological indicators such as trust or commitment, behavioral indicators such as usage or contact frequency, and economic indicators such as revenue or profit. Typically, relationship marketing research assumes these constructs to be related in an impact or success chain (Heskett et al., 1994; Storbacka et al., 1994) where these are growing together by linear progression (Bendapudi and Berry, 1997; Egan, 2001; Palmatier, 2008). And in particular that "customers generate increasingly more profits each year they stay with the company" (Reichheld and Sasser, 1990, p. 106). As already outlined in Chapter 1, this notion is enjoying widespread acceptance almost to the point of a generalized direction, making it even more important to reemphasize that this is an *ideal-type* development. In reality, the development and the interrelation of these constructs is much more complex. Therefore, the contrasting of these propositions with actual empirical findings through a descriptive lens in the next chapter is particularly important.

2.5.3 Empirical Contributions

2.5.3.1 Behavioral Sources of Customer Value

The aim of all marketing initiatives ultimately is to maximize customer value in the form of CLV (Bell et al., 2002). However, as a retrospective measure abstracted from actual observable and manipulable behavior and actions, CLV cannot be operationalized for strategic marketing management. Additionally, the trend in customer profitability reflects the evolution of the customers' attitude towards the relationship in its exchange characteristics (Dwyer et al., 1987; Ganesan, 1994). So it is important to look at the specific relational purchase behavior rather than at profitability as an aggregate.

Accordingly, in order to be managerially relevant, investigations must identify the drivers of customer value and establish links between manipulable (marketing instruments) and observable (customer behavior) antecedents of customer value. For this task, several frameworks have been proposed, such as the '*Return on*

Marketing' (Rust et al., 2004) or the '*Customer Asset Management of Services'* (CUSAMS; Ruth N. Bolton, Katherine N. Lemon, and Peter C. Verhoef 2004) framework. For this dissertation the latter is preferable because it incorporates several concrete aspects of customer behavior rather than just attraction and retention in the former.

Analogous to Rappaport's three main drivers of shareholder value (compare section 2.3.1), one key insight of the CUSAMS framework is that the source of CLV ultimately is a combination of the three behavioral dimensions of customer–firm relationships: length, depth, and breadth. These behavioral sources can be operationalized as actual observable customer behavior which directly relates to CLV through the revenues that they generate for the firm as displayed in Figure 12: Therein, duration is defined as churn (i.e., the fraction of customers who terminate or continue the relationship with the organization), usage as transaction frequency and spending level per transaction, and cross-buying as the number of different categories of products or services purchased over time.

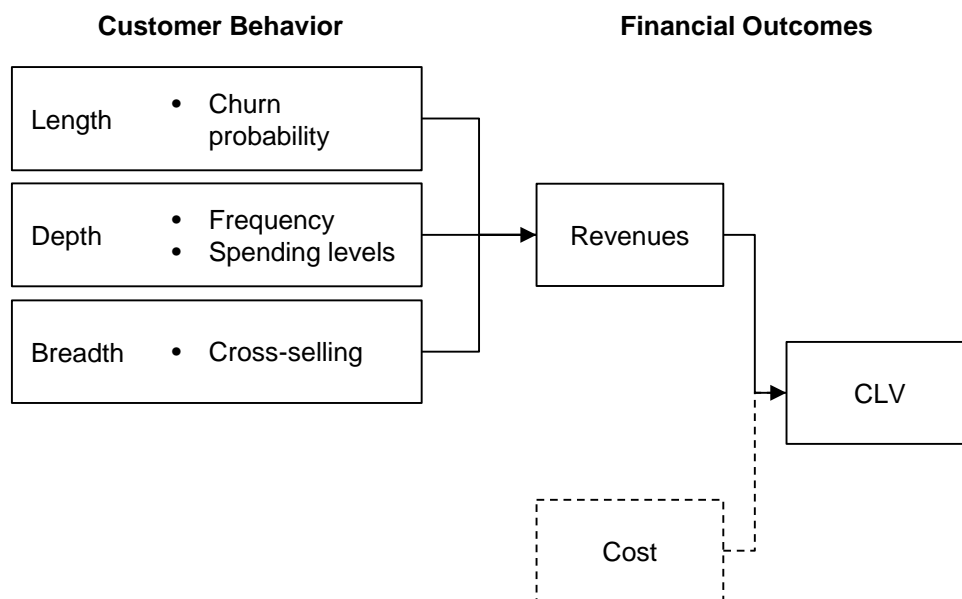


Figure 12: Conceptual Model of Customer Lifetime Value

Source: Own Illustration based on Bolton, Lemon, and Verhoef (2004)

In this dissertation I focus on the revenue part of CLV. In most contexts, the full costs associated with the marketing exchange are difficult to allocate precisely to specific customers. In practice, typically only specific parts of the costs are tracked

(e.g., mailing costs), rendering a complete and reliable empirical analysis impossible. Here, existing research is often confined to promotional costs. In this regard, no substantial differences have been found between customers with long and short tenure (Reinartz and V. Kumar, 2000a).

2.5.3.2 Meta-Analysis of Research Findings on the Behavioral Sources of Customer Value

Propositions regarding the development of customer profitability and its behavioral sources are often denoted as "tenet" (Reinartz and V. Kumar, 2000a, p. 17) or "contention" (Dowling and Uncles, 1997, p. 14) hence implicitly promising the normative and predictive quality of an empirical generalization¹⁵. According to Blattberg, Briesch, and Fox (1995, p. G123), an effect can be considered an empirical generalization if "(1) the topic being analyzed is well-defined; (2) there are at least three articles by at least three different authors in which empirical research has been conducted in the specific area; and (3) the empirical evidence is consistent, i.e., the sign of the effect is the same in each of the articles".

I identified 12 empirical studies that investigated the development of customer profitability or its behavioral sources over time. Table 3 summarizes their findings. It is strikingly apparent that a considerable amount of conflicting findings on the developmental trend of customer profitability and its antecedents exists. Thus, current factual knowledge does not hold the normativity simply due to a lack of consistent findings in support (as claimed in requirement 3). Furthermore, the 'tenet' of increasing profitability falls short of the hurdle for generalization because in some regards it does not sufficiently meet the criterion of well-definedness. This is because, as stated, these studies differ widely in research methodology, some address profitability only as an aggregate or focus on a specific subset of its antecedent behavioral sources (Bolton et al., 2004), and others are based on a small number of customer datasets from particular contexts. Thus, they exhibit more of a case study character.

¹⁵ I follow Bass (1995, p. G6) and define an empirical generalization as "a pattern or regularity that repeats over different circumstances and that can be described simply by mathematical, graphic or symbolic methods".

Table 3: Findings of Previous Studies

Study	Churn	Revenue	Frequency	Spending level	Cross-buying	Cost	Profits	Datasets
Reichheld and Sasser, 1990		+	+	+		-	+	- Credit cards ^C - Industrial laundry ^{NC} - Industrial distribution ^{NC} - Auto service ^{NC}
Schmittlein and Peterson, 1994			-					- Office supply ^{NC}
Li, 1995	+							- Telco ^C
Hallowell 1996							+	- Retail banking ^C
Reinartz and Kumar, 2000b				-		n/s	+/-	- Catalog retailer ^C
Niraj et al., 2001						+	-	- Grocery distributor ^{NC}
Reinartz and Kumar, 2003			-	+	+			- Catalog retailer ^{NC}
Fielding, 2005	-							- Newspaper ^C
East et al., 2006				+/ n/s				- 17 datasets ^{11NC, 6C}
Jamal and Bucklin, 2006	+							- Pay TV ^C
Borle et al., 2008	+		-	+				- Membership-based direct marketer ^{NC}
Schweidel et al., 2008	+							- Telco ^C

Note. + = increasing trend found; - = decreasing trend found; C = contractual context; NC = non-contractual context; n/s = not significant; only first order effects are reported.

2.5.4 Necessity for Further Research

The implicit assumption in customer relationship models of monotonic increasing relationship strength growing together with relational constructs such as trust or commitment over time and, hence, producing increasing profits is shared in much of the relationship marketing research (Bendapudi and Berry, 1997; Palmatier, 2008, p. 36; Reichheld and Sasser, 1990; Reichheld and Teal, 1996). In many cases the argumentation bases on Reichheld and Sasser (1990) and Reichheld and Teal (1996) and their prominent illustration of how additional profits from ever increasing purchase frequency, spending levels, price premium, referrals, and reduced cost of servicing the consumer over time add up to a multiple of the initial base profits (Figure 1).

However, there is also growing evidence that this common trajectory of relationship maturity and financial outcome might not hold and in reality is far more complex (Bolton et al., 2004). For example, Moorman, Zaltman, and Deshpande (1992) and Grayson and Ambler (1999) find a 'dark side' of long-term relationships and point out that trust and commitment do not always translate into increasing usage when a relationship moves into later stages. Gruen, Summers, and Acito (2000, p. 44) suggest that actors in a long relationship develop a "what have you done for me lately?" attitude, which paradoxically leads to an increasing short-term focus in terms of cost and benefits. In fact, Hibbard and colleagues (2001) found the impact of all these constructs on relationship performance to decrease over time.

Also Verhoef and Langerak (2002, p. 73) warn "that it is a gross simplification to equate loyal customers with higher profits." Likewise, also Dowling and Uncles (1997) caution against the assumption of a clear-cut positive lifetime-profitability relationship and underline the importance of a differentiated analysis. Also the results of my meta-analysis highlight that there is a gap between the normative propositions and the actual observed findings on the development of customer profitability and its behavioral sources over the course of the customer-firm relationship.

At the same time however, the conjecture that customers become more profitable over time continues to enjoy widespread acceptance in academic research,

marketing textbooks (Bruhn, 2002; Kotler and G. Armstrong, 2010) and managerial guides alike (Hughes, 2006; Reichheld and Teal, 1996; Schenck, 2005). Even in practice, this proposition has found its way into general directives that serve to steer several corporate functions. Managers widely use it as a foundation for marketing strategy formulation and its justification for shareholders (CQ Transcriptions LLC, 2010a; b; c). In this context, critics have argued that "research to date appears highly selective (Reichheld and Teal, 1996) and all too frequently designed to support a particular (often consultant based) perspective" (Egan, 2001, p. 375), which they attribute to the enormous popularity that relationship marketing is experiencing and academics' "lemming-like" devotion to the relational paradigm (S. Brown, 1998, p. 171). It seems, that "the existing literature is replete with unsubstantiated principles" (S. W. Brown et al., 1994, p. 41) such as a link between customer satisfaction, loyalty, and profits or the tenet of increasing customer profits over time which are being adopted despite "[relationship marketing] theory appears to have very little in the way of empirical observation of relationships over time to support it" (Egan, 2001, p. 375).

Given the high relevance of this tenet despite the conflicting evidence, there is an urgent need for further research on this topic. In the next chapter, I develop a research methodology aiming to improve on this situation by (1) basing my analysis on a solid empirical foundation, (2) analyzing the antecedents of customer profitability comprehensively, and (3) developing a holistic and stringent research design from a discussion and synthesis of methodologies from previous studies.

3 Empirical Review of the Development of Customer Profitability

3.1 Introduction

In the previous chapter I identified the great importance of the developmental trend in customer profitability. I also pointed out that though the conjecture that customers become more profitable over time is widely accepted, still a considerable amount of conflicting findings remain. Consequently there is an urgent need for further research.

This chapter is dedicated to reviewing this tenet and answering the first research question. I will start by discussing findings on these behavioral sources of customer profitability. On most aspects, there exists a considerable amount of conflicting results. Therefore, I do not develop concrete and directed hypotheses, but rather define a further set of (undirected) research questions regarding the developmental trend of customer behavior. I will answer them by analyzing a sample of six customer datasets from various industries in business-to-consumer contexts and examining the slope coefficients of the regression.

3.2 Specification of Research Questions

3.2.1 Duration

Predicting churn probability is one of the main challenges in customer management (Fader and Hardie, 2009; Nath, 2003; Schweidel et al., 2008). Insights from customer data analyses influence a wide range of corporate functions and activities, such as general marketing, complaint management, and even company valuation. Typically, models for predicting churn assume a decreasing churn

probability over customership duration (Fader and Hardie, 2009). This trend is often explained with the inertia of habitual buying behavior and transaction cost theory, attributing decreasing churn rates to switching costs that build up over the customer relationship. With increasing tenure, the customer becomes familiar with the company's product offering and processes and develops trust in the company (Reinartz et al., 2008; Verhoef and Langerak, 2002). Bolton (1998) adds a social exchange perspective to this argument and states that—to the extent that a customer's past experience with the company is positive—churn probability decreases over the relationship duration.

However, for many of these relational benefits to come to into play, a social relationship of some form must exist in the first place. In this context, Gwinner and colleagues (1998, p. 111) acknowledge, that "for larger organizations (e.g., national hotel chains and airlines) this can be more difficult". But even if firms manage to establish a relationship with their customers, many arguments for increasing churn probability exist. According the social exchange theory, it could also be argued that because in many contexts long-term customers are more sensitive to (inevitable) unsatisfactory experiences (Grégoire et al., 2009; Heumann et al., 2010), they are more prone to defection (compare section 2.4.7). Also, contrasting the notion of continuously decreasing churn rates is an intuitive consideration based on the product and customer life cycle: neither products nor customers are 'immortal', which constantly decreasing churn rates would imply. Indeed, Schweidel, Fader, and Bradlow (2008) as well as Jamal and Bucklin (2006) find that churn generally increases over time. In other studies, churn probability has been shown to sharply increase after a certain amount of time (Borle et al., 2008; Li, 1995).

In the light of these arguments and empirical evidence for both decreasing and increasing churn probability, I present the following research question.

RQ_{1a}: Does the churn probability of customers change with increasing tenure, and if so, what is the direction of this effect?

3.2.2 Purchase Frequency

In managerial practice, purchase frequency is a key exchange characteristic (Hughes, 2006). Conceptually, it is often viewed as an expression of relationship strength that grows as customers become accustomed to the product or service and the company itself (Reichheld and Sasser, 1990; Reinartz et al., 2008; Reinartz and V. Kumar, 2003). Thus, frequency should increase over time. As for churn probability, Morgan and Hunt (1994a) argue with social exchange theory that frequent satisfactory interactions lead to greater trust, which in turn should lead to greater relationship durations. Last, basic intuition indicates that as the customer's relationship with a company matures, the company will receive a higher share of the customer's wallet, which materializes in increasing purchase activity (Reinartz and V. Kumar, 2003).

Though Reinartz and Kumar (2003, p. 82) in general agree with the notion of increasing purchase frequency over time, they also caution that highly active customers might have "a rather short lifetime because the customer has stocked up on items". This would imply a form of wearout that leads to an inverse U-shaped relationship between relationship duration and frequency. Likewise could be argued with learning and risk theory (compare sections 2.4.4 and 2.4.5): with increasing usage, customers might 'venture' into transactional buying to offset boredom. And as users gather experience the perceived risk decreases. Thus, they feel more confident purchasing from new providers.

Again, I find contradicting arguments for the direction of the development of purchase frequency. Accordingly, I formulate the following research question:

RQ_{1b}: Does the purchase frequency of customers change with increasing tenure, and if so, what is the direction of this effect?

3.2.3 Spending Levels

In many industries, it is general practice for companies to attract customers with low or even waived fees only to raise prices over time (e.g., telecommunications, credit cards; T. J. Smith, 2011, p. 125). This practice goes back to the tenet that

customers become less price sensitive over time (Reinartz and V. Kumar, 2002). As a customer acquaints himself with the company's processes and product offering, he will almost invariably receive greater benefits from the business relationship. From a customer's perspective, value can be conceptualized as the difference between perceived product price and perceived quality (Zeithaml, 1988). Thus, with increasing value from the business relationship, the customer should also accept higher prices and become less price sensitive (Reichheld and Teal, 1996). Reinartz and Kumar (2000, p. 21) also highlight that loyal customers have a higher level of awareness of the firm and, therefore, are "likely to pay higher prices than new or frequently switching customers"—an effect especially witnessed in the domain of e-commerce (Brynjolfsson and M. D. Smith, 2000). Another factor contributing to higher spending levels of longer-term customers is the greater opportunity for firms to up-sell to these loyal customers (Parvatiyar and Sheth, 2001). Customers who chose an entry-level product for their first purchase might follow up-selling paths and upgrade with their subsequent purchases.

However, in contrast with these arguments, is informal experience of practitioners who often witness a higher value consciousness of long-term customers (Reinartz and V. Kumar, 2000a). Reinartz and Kumar (2000a) endorse this observation in their study on the link between customer loyalty and profitability. They find that certain short-life customers pay higher prices than long-life customers. An argument in support of this development draws from learning theory (compare section 2.4.4). It states that more loyal customers have more experience with the product portfolio and, consequently, develop solid reference prices, enabling a more focused and targeted spending behavior. Similarly, Reinartz and Kumar (2000a) suspect, that with increasing experience customers learn to trust lower priced items or brands rather than relying on brand names as signal for quality (compare section 2.4.5). In addition, surveys consistently show that, in general, consumers expect more loyal customers to receive amenities and punish increasing prices by terminating the relationship (Reinartz and V. Kumar, 2002).

Also for the development of customers' spending levels, evidence exists for both a decreasing and increasing trend. Thus, I accordingly formulate the following:

RQ_{1c}: Do spending levels of customers change with increasing tenure, and if so, what is the direction of this effect?

3.2.4 Overall Revenues

The overall revenue of a customer is ultimately a result of purchase frequency and spending levels. Hence, the above (conflicting) arguments also apply for the expected trend in the overall revenues, leading to the following research question:

RQ_{1d}: Does the overall revenues of customers change with increasing tenure, and if so, what is the direction of this effect?

3.2.5 Cross-Buying

Cross-buying is the purchase of products or services from different categories (Blattberg et al., 2008). It is often described as being positively related with customer tenure. In the literature, this interrelation is explained in two ways. First, from a behavioral point of view, cross-selling increases with customer tenure because as customers build up trust in and commitment to the firm, they broaden their relationship with it (Reinartz et al., 2008). In this context, cross-buying is also described as "scope of interaction" (Reinartz and V. Kumar, 2003, p. 81), which constitutes an important dimension of a relationship. And as Kelley and Thibaut (1978, p. 234) argue with social exchange theory, as relationships intensify, the parties will also expand the scope of their relationship (compare section 2.4.7).

Second, according to transaction cost theory (compare section 2.4.2), cross-buying can also be considered causal to customer tenure: cross-buying reflects the customer's familiarity with the company's product offering, which constitutes switching cost for the customer and, hence, decreases his propensity to terminate the relationship (Reinartz et al., 2008). An argument in support of this causality is based on subjective utility theory (R. L. Oliver and Winer, 1987), which predicts that customers maximize the utility obtained from a given vendor. According to this reasoning, buyers who purchase from several categories are those that experience great utility across many categories and, thus, are less prone to

defection (Reinartz and V. Kumar, 2003). Or stated differently: one would suppose a high fit between a customer's needs and the firm's offering if the customer buys across many categories.

Regardless, I expect a positive correlation between cross-buying and customer relationship duration. For consistency reasons, I nevertheless formulate an undirected research question:

RQ_{1c}: Does cross-buying of customers change with increasing tenure, and if so, what is the direction of this effect?

3.3 Research Design

3.3.1 Research Context and Data

Though claims about the development of customer profitability and its behavioral antecedents are often generalized, it has been argued that these trends are at least to some extent context and industry specific (Blattberg et al., 2009). In particular, different characteristics of contractual and non-contractual contexts (Wübben and v. Wangenheim, 2008) and business-to-consumer and business-to-business markets (Palmatier et al., 2006) could lead to some variations.

Acknowledging this context specificity, I focus my analysis and constrain my investigation to the business-to-consumer context and consider contractual and non-contractual contexts separately. In total, the study is conducted on the customer databases of six service companies from various fields: a major European airline (n = 11,218), a major German multibranch hardware store (n = 20,146), a large German multibranch fashion retailer (n = 18,675), a large German multibranch general merchandise retailer (n = 29,221), a major German internet service provider (ISP; n = 33,675) and a large German telecommunications service provider (telco; n = 6,875). The first four datasets are from a non-contractual and the latter two from a contractual context. All datasets represent longitudinal data and capture the activities of the included customers

over time with repeated observations. To my knowledge, with six datasets, my study represents the largest systematic empirical analysis in this domain.

In line with many other studies, I use a cohort-based analysis. Cohort analysis is a form of observational study which is very common in social sciences and medicine. It investigates a group of subjects with a common characteristic with longitudinal measurements as depicted in Figure 13 (Menard, 2002). In the case of this study, the common characteristic is the first purchase date. I track customers having their first purchase within a certain interval from this time onward. To further validate my results and e.g., exclude seasonal effects, I additionally track and analyze customers in a second cohort. Customers in the first cohort purchased in the first period of observation, and customers in the second cohort purchased in the second period¹⁶.

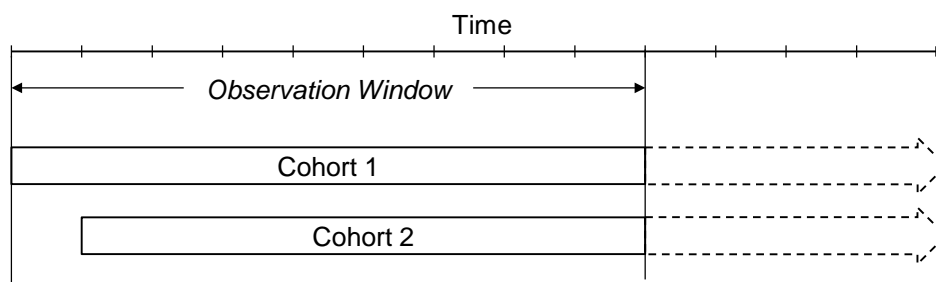


Figure 13: Cohort-Based Analysis
Source: Own Illustration

The advantage of this cohort-based approach is that because it follows customers through time, it can disentangle interpersonal differences and general trends. In contrast, when analyzing tenure effects cross-sectional studies are always potentially biased by interpersonal differences. This is most easily illustrated using an example: suppose a researcher would want to test the hypothesis that people use the internet less as they grow older. In a cross-sectional design he would survey individuals of different ages and compare internet usage of younger respondents with older respondents. If the older respondents reported a lower internet usage he might indeed conclude that the hypothesis of decreasing internet usage is true. However, there is another plausible explanation. Perhaps

¹⁶ I conducted the analyses testing several period intervals to guarantee a high validity, i.e. with regard to possibly differing seasonalities.

older respondents in the sample always exhibited very low and younger always very high internet usage. In other words: cross-sectional differences by age may be confused with differences that result from increasing tenure or experience. Therefore, a cohort-based approach which would measure internet usage per individual with repeated observation over time is preferable for studying developmental trends across the customer life cycle (Menard, 2002; Reinartz and V. Kumar, 2000b).

In Table 4, I provide descriptive information of customers in the first cohort for all datasets. In favor of a better readability, I only show the data for the first cohort of each dataset in the main part. The respective information about the second cohort can be found for reference in Appendix A.1.

Table 4: Description of Datasets (Cohort 1)

	Airline	Hardware store	Fashion Retailer	General Retailer	Telco	ISP
Time span	13 qtrs	12 qtrs	8 qtrs	7 qtrs	9 qtrs	8 qtrs
Number of customers	6,065	11,543	11,004	19,676	4,795	24,567
Ø trans./ cust. p.a.	8.3 (δ 7.6)	15.8 (δ 13.1)	6.4 (δ 6.3)	10.9 (δ 11.8)	n/a	n/a
Ø revenue/ trans or mth	€ 207 (δ 207)	€3 7.3 (δ 77.7)	€ 117 (δ 165)	€ 98,5 (δ 144)	€ 87,3* (δ 199)	€ 16.8* (δ 23.5)
% right censored	28%	74%	79%	72%	74%	87%

Note. Qtrs = quarters; n/a = not applicable; * = overall per month; δ = standard deviation

3.3.2 Determination of Active and Inactive Customers

For all analyses, I need to distinguish between active and inactive customers. Whereas in the contractual context the actual lifetime is generally known, the situation in the non-contractual context is far more complex. If a customer stops purchasing, there is no way of knowing whether this is just a temporary pause and this customer will conduct business in the future or if this customer terminated the relationship with the firm (Reinartz and V. Kumar, 2000a). In particular, given

the limited observation window, if a customer after a certain number of purchases does not purchase again for the rest of the observation window, I need to determine whether to treat the customer as inactive or whether to expect him to purchase again after my observation window and as a result treat him as active. For this task, several approaches have been proposed, the most prominent in the academic literature being the Pareto/NBD (Schmittlein et al., 1987; Schmittlein and R. A. Peterson, 1994) and the BG/NBD model (Fader et al., 2005).

Both are stochastic models and yield—among others—a probability that a customer is still active at a given time, based on this customer's past purchase behavior. The first model bases on the assumption that purchases follow Ehrenberg's NBD model and churn events follow an exponential gamma (Pareto) distribution; and the latter that churn events follow a beta geometric (BG) model¹⁷. However, both models need to be calibrated on the customer base in a rather complex process. In managerial practice, simple heuristics are still being applied (Verhoef et al., 2002). Wübben and v. Wangenheim (2008) even show that these simple recency heuristics perform at least as well as stochastic approaches such as the Pareto/NBD or the BG/NBD model.

To foster transfer of my results to practice and in line with Wübben and v. Wangenheim's (2008) finding, I use a simple recency-of-last-purchase (hiatus) analysis to distinguish active from inactive customers. This simple heuristic considers customers who have not purchased for a given period inactive. In practice, managers use their expert knowledge of the domain to choose the cutoff period. To maximize precision, I optimize the threshold per dataset with a simple algorithm, as Wübben and v. Wangenheim (2008) suggest. In a first step, I split the datasets into two halves, with the first being the train and second the test dataset. In a second step, I iterate over all valid cutoff thresholds, apply it to the train dataset, and evaluate the resulting precision (i.e., the fraction of correctly classified customers as recorded in the test dataset). When applying the optimal cutoff thresholds, I achieve good accuracy throughout all the datasets of 75%–90% (see Table 5).

¹⁷ The basic difference in assumption of this model to the Pareto/NBD model, is that the dropout occurs only directly after a purchase, which allows the use of the BG model and, thus, greatly reduces complexity.

Table 5: Parameters and Accuracy of Hiatus Heuristic

	Airline	Hardware Store	Fashion Retailer	General Retailer
Optimal cutoff threshold	4 quarters	11 months	50 weeks	31 weeks
Correctly classified	75.6 %	89.3 %	75.0 %	76.7 %

While not evident on the aggregate level, at the individual level in some instances I observed very long temporal inactivity. Temporal inactivity is problematic if the customer is inactive longer than the cutoff threshold—leading to the classification as "inactive"—but starts buying again. Given the long purchase histories of up to 13 quarters and in line with the always-a-share model (compare section 2.3.2), I allow for these long periods of inactivity and encompass the entire available customer history for the calculation of the total lifetime. Though this is the case only for very few customers (Airline 5.33%; Hardware Store .88%; Fashion Retailer 2.74%; General Retailer 3.40%; \emptyset 3.09%), this procedure might induce a statistical artifact causing a bias of the analysis. This is because for later periods the prevision window becomes shorter, hence also the probability of detecting this misclassification. The extent of this artifact depends on the prevalence of the resurgences and their distribution after the cutoff threshold. The prevalence is considerably low with an average of 3.09% as stated. For the distribution of interpurchase times, in marketing typically two models have been used at the individual level: the exponential and the Erlang-2 distribution (S. Gupta, 1991). Because the probability density functions of both distributions asymptotically approach zero, for sufficient large intervals from the previous purchase incidence small differences in observation window can be neglected.

3.3.3 Analysis of the Behavioral Sources of Customer Value

3.3.3.1 Remarks on the Overall Approach

As numerous as the studies on the development of customer profits over time are the employed methodologies. Reichheld and Sasser (1990) in the probably most prominent article on this topic for example use a very basic and intuitive approach. They discuss the development of customer profitability over time based on customer revenue graphs and their growth rates. More common, however, are

basic statistical methods such as group comparisons, correlations analyses and OLS regressions (East et al., 2006; Hallowell, 1996; Reinartz and V. Kumar, 2000a, 2002). Reinartz and Kumar (2000a, 2002) for instance, in a first analysis segment the customer base with a split of the median customership duration and compare average profits. In a second analysis they use OLS regression to test the developmental trend. Another common approach is survival analysis (Jamal and Bucklin, 2006; Li, 1995; Reinartz and V. Kumar, 2003; Schweidel et al., 2008). Conceptually assuming an inverse causal relationship (see Appendix A.2), these studies test the impact of several behavioral and demographic covariates on the lifetime duration. Moreover, on a statistically more sophisticated end, some authors have also used, e.g., a hierarchical Bayes approach (Borle et al., 2008) and complex probabilistic models (Schmittlein and R. A. Peterson, 1994).

Principally, this variety of approaches strengthens the robustness of the findings towards generalizability. However, only in few instances has an aspect under investigation been analyzed with the same methodology. Since the results of many methodologies are not straightforward to understand (especially for practitioners) and to compare among each other, this methodological variety at the same time also hampers comparability of results and transferability to practice. Furthermore, the plethora of studies not only varies with regard to methodology, but also with regard to scope, because as stated—to the best of my knowledge—no study exists investigating the trend of sub-drivers of profitability comprehensively. Due to their interdependence this however is essential. Rather studies either analyze profitability as an aggregate or focus on specific aspects (compare section 2.5.3.2).

As reflected earlier, contractual and non-contractual contexts differ. Especially the present analysis of the behavioral sources of customer value has to acknowledge that if buyer-seller relationship is governed by a contract, the usage patterns, spending levels (i.e., prices), and to some extent even the relationship duration might be predetermined (Wübben and v. Wangenheim, 2008). Additionally, whereas the non-contractual setting is often characterized by discrete transactions with specific revenues, various different tariff structures in the contractual context impede a meaningful analysis: base fees, inclusive volumes and usage dependent prices oftentimes preclude the allocation of revenues to specific transactions. Therefore, in this dissertation I analyze the behavioral sources of customer value

in the contractual setting on an aggregated level (i.e., duration and overall revenues). For consistency reasons and to allow comparisons of results, I likewise analyze these aspects in the non-contractual context additionally on an aggregated level.

In order to paint a comprehensive and consistent picture of the developmental trend of all behavioral sources of customer value, this dissertation bases all analyses on a common and basic method. Also in an effort to foster transferability to practice, I will base on the conceptually easily comprehensible and in practice widespread linear regression. Taking 'Einstein's razor' as guiding principle that states in essence, that everything should be as simple as it can be (but not simpler), I use this parsimonious approach and extent it where necessary, drawing from experience and insights of existing studies.

3.3.3.2 Churn Probability

I analyze churn at the firm level, which is the percentage of a company's active customer base that becomes inactive during a certain period (Blattberg et al., 2008; Fader and Hardie, 2007). For the churn analysis, right censoring needs to be accounted for (see Figure 14). Right censoring occurs if a customer's churn event is missed due to a limited observation window or because he is discarded from the study before churning (e.g., in case of the telco, because the contract is suspended for an indefinite time).

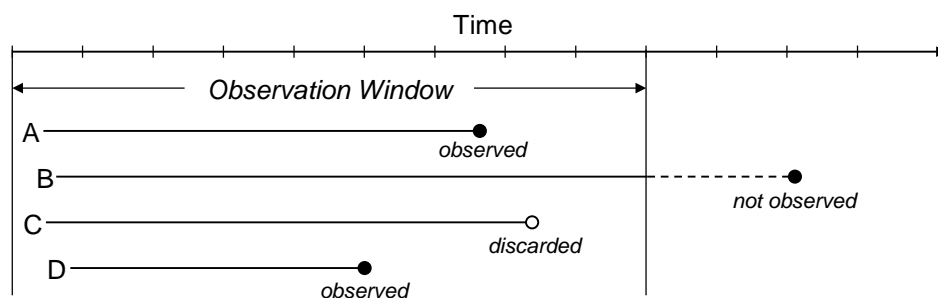


Figure 14: Right Censoring
Source: Own Illustration

In contexts with right censoring, researchers oftentimes use survival analysis which can handle censored data effectively (Hosmer et al., 2008). I will give a more detailed introduction to survival analysis in Appendix A.2; for this section it is sufficient to note that for a univariate analysis (i.e., devoid of any covariate effects) the simple *Kaplan-Meier product limit estimator* can be used (Kaplan and P. Meier, 1958). Based on the Kaplan-Meier product limit estimator, churn probability can be formulated taking account of right censored data as:

$$churn(t) = \frac{d_t}{n_t} \quad (3.1)$$

where

d_t = churn observations in period t , and

n_t = number of customers 'at risk' in period t , excluding censored observations.

By adjusting the denominator n_t to exclude censored observation only at the point of censorship, this estimator allows each subject to contribute information to the analysis as long as it is known to not have churned. Customers that have an observed churn event contribute to the number at risk until they churn at which point they contribute to the number of churn observations. Customers with censored observations contribute to the number at risk until they are lost for follow-up (Hosmer et al., 2008, p. 19).

For each cohort, I calculate the churn rates per period after the first purchase and examine the sign of the linear slope coefficient. In the non-contractual context, for almost all the datasets a peak of churn in the first period exists, which reflects a high share of one-time buyers. Likewise in the contractual scenario, for customers of some plans in the telco dataset, small peaks in the churn rates after minimum cancelation periods can be observed. To adjust for this peak in the linear regression, I follow Reinartz and Kumar's (2000a) recommendation to include a dummy variable that absorbs the effect of one-time buyers and bursts after minimum cancelation periods. The exact specification of the linear regression is as follows:

$$churn(t) = \alpha + \beta_1 t + \beta_2 dummy_{peak} \quad (3.2)$$

where

$churn(t)$ = as defined in equation (3.1),

t = period of observation after first purchase (i.e., quarter or month),

α = intercept,

β_1, β_2 = regression coefficients, and

$$dummy_{peak} = \begin{cases} 1 & \text{if first period, 0 otherwise} & \text{non-contractual} \\ 1 & \text{if min contract duration, 0 otherwise} & \text{contractual} \end{cases}$$

As stated previously, in a non-contractual context I can only approximate churn with (long) customer inactivity. But as an upper boundary, this measure should realistically reflect trends in the actual churn.

3.3.3.3 Purchase Frequency

Previous studies have modeled purchase frequency with two constructs, both of which can be translated into the other¹⁸: transactions per period and interpurchase time. Especially for contexts with sporadic purchase behavior (as is the case for the airline or hardware store), interpurchase time is preferable. This is because (1) the transactions-per-period approach tends to overweight inactive periods, since the many consecutive inactive periods would each result in a zero in the regression versus only one long interpurchase time. And (2), in a cohort-based approach, the transactions-per-period construct introduces an artifact that would also need to be adjusted for: by definition, all customers in a cohort purchase in the first period, so, on average, the number of transactions in the first period will be significantly higher than in the following periods, in which idle customers reduce the average.

In order to investigate the dynamic aspect—that is, the developmental trend over customer relationship duration—I need to isolate this trend from effects due to customer heterogeneity. Customer heterogeneity expresses itself in a multitude of factors that cannot be controlled for completely (e.g., professional travel requirements, disposable income, household size). Because these factors are typically constant, they also have a constant effect that results in time-invariant

¹⁸ Although when interpurchase times are translated into transaction per period, some precision is lost.

customer-specific differences in the overall level of purchase activity. In some datasets (e.g. the airline), I even find a correlation between these levels and the customer relationship duration length. In retrospect, customers who stayed with the company for a long period, tended to overall be more active than short-life customers, notwithstanding the developmental trend.

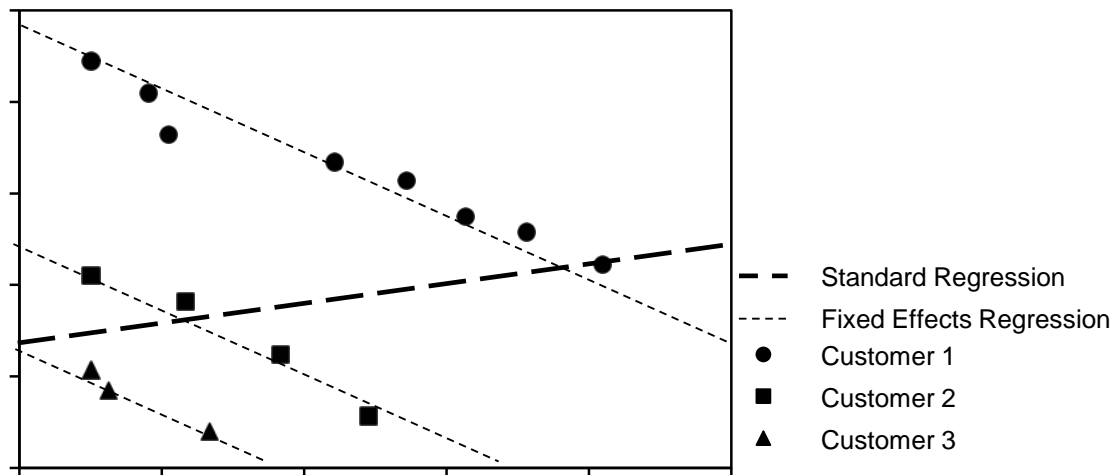


Figure 15: Conceptual Comparison of Standard and Fixed Effects Regression
Source: Own Illustration

As shown in Figure 15, if not controlled for, this effect could bias my results due to a sorting effect. To isolate this from customer-specific stable differences, I use fixed-effects regression. By introducing a unit specific intercept α_i for each customer i in the regression equation, I can absorb all stable characteristics of this customer i (Greene, 2008). In line with previous studies and because of its intuitive nature, I use fixed effects with linear regression, which gives the following exact specification:

$$it_i(t) = \alpha_i + \beta_1 t \quad (3.3)$$

where

$it_i(t)$ = interpurchase time of customer i at time t ,

t = time of observation after first purchase (i.e., quarter or month),

α_i = intercept of customer i , and

β_1 = regression coefficient.

3.3.3.4 Spending Levels

I operationalize spending levels as revenue per transaction, which reflects both price sensitivity and up-/down-selling. This aggregate measure is often used as operationalization of value consciousness in direct marketing (Nash, 2000, p. 54). Due to the long observation window of up to three years, changes in customer spending levels need to be isolated from general trends in prices. Inflation, increase in taxes, dues, and other external effects might become relevant influences that need to be controlled for. Therefore, I normalize the spending levels in a certain period with the average revenue per transaction of all first-time customers in this period. By specifically choosing only first-time customers for normalization, self-cancellation or enforcement of the hypothesized trend due to possible shifts in the firms' customer base tenure compositions can be avoided.

To separate spending levels from changes in purchase frequency, I only consider active periods of a customer. Inactive periods are not considered in the regression. Additionally, also for spending levels, I apply linear fixed-effects regression to absorb uncontrolled stable customer characteristics (Greene, 2008). Thus, the linear fixed-effects regression equation is as follows:

$$spend'_i(t) = \alpha_i + \beta_1 t, \quad (3.4)$$

where

$$spend'_i(t) = \frac{spend_i(t)}{\{spend_j(t) | birth(j) = t\}},$$

$spend_j(t)$ = average revenue per transaction of customer i in period t ,

t = time of observation after first purchase (i.e., quarter or month),

α_i = intercept of customer i , and

β_1 = regression coefficient.

3.3.3.5 Overall Revenue

For most datasets the available revenue data is aggregated on a per-period base rather than per concrete transaction. Consequently revenue data must also be analyzed per period. However, especially in the non-contractual context purchase

behavior is arbitrary and sporadic and, hence, many periods with zero revenues exist. In this situation it can be misleading to focus on the overall revenue per period (v. Wangenheim and Lentz, 2005). For three out of four datasets of the non-contractual context, customers are active in less than half of the periods. This excessive number of zeros is a common phenomenon in datasets involving human behavior. Many methods to cope with this issue have been proposed—neither of them being without disadvantages. Most common approaches can be broadly classified in three classes (Bahn and Massenburg, 2008): (1) specific zero-inflated or two-part models, (2) imputation of the zeros in the analysis (e.g., by considering them as missing data), or (3) transformation of the response variable.

Especially for count data, researchers use statistically sophisticated zero-inflated models (Greene, 2008; Lambert, 1992). Zero-inflated models account for excess zeros by assuming the data to be a result of two different processes: a first process produces a binary outcome, where with probability of p a zero is observed; and with probability $1 - p$ the random variable of the second process is observed (typically a Poisson variable). For example, when investigating car accidents of novice drivers, zeros could be due either because a novice does not drive at all or because he is a careful driver. This implicit assumption of two processes might, however, not always be appropriate. V. Wangenheim and Lentz (2005) for example, use a combination of the latter two approaches. For one, they use a conditional revenue variable and consider only periods on the condition that a user generated revenues in this period. When analyzing developmental trends in customer revenues, this approach is accurate, however, only under the assumption that inactive periods are uniformly distributed over time. Therefore, they additionally inspect revenues aggregated to longer timeframes where the problem of inactivity is much less severe, however at the cost of loss of sampling frequency.

Given the long observation window in my datasets and the aim for parsimony, the approach of aggregating periods to longer time-frames seems well suited for this analysis. In particular, I aggregate periods to half-year periods where necessary, which significantly reduces inactive periods while still preserving sufficient sampling points (see Table 6).

Table 6: Purchase Inactivity in Non-Contractual Datasets

	Share of Inactive Periods			
	Airline	Hardware Store	Fashion Retailer	General Retailer
Before aggregation	55.3%	42.8%	59.3%	51.5%
After aggregation	29.7 %	– ¹	23.5%	33.2 %

Note. ¹ = hardware store not aggregated due to already sufficient activity.

As for the analysis of spending levels, in the non-contractual contexts, trends in overall revenues need to be isolated from general trends in prices, as mentioned before. In contractual contexts, prices are often predetermined for the contract duration; hence changes in market prices propagate less quickly. Accordingly, in the non-contractual contexts, I normalize revenues per transaction in a certain period with the average revenue per transaction of all first-time customers in this period. Similar to the analysis of purchase frequency, also for overall revenues I apply linear fixed-effects regression to absorb uncontrolled stable customer characteristics (Greene, 2008). Thus, the linear fixed-effects regression equation is as follows

$$revenue'_i(t') = \alpha_i + \beta_1 t' (t), \quad (3.5)$$

where

$$revenue'_i(t') = \frac{revenue_i(t')}{\{spend_j(t') | birth(j) = t'\}},$$

$revenue_i(t')$ = revenue of customer i in period t' ,

$spend_j(t')$ = average revenue per transaction of customer j in period t' ,

t' = period of observation (i.e., half year),

α_i = intercept of customer i , and

β_1 = regression coefficient.

3.3.3.6 Cross-Buying

In line with previous studies, I operationalize cross-buying as categories purchased per period. In particular, I follow an understanding of cross-buying that specifically does not require two purchases in different categories to occur at the

same purchase incident to qualify as cross-buying. Rather, I also allow short intervals in between. Given the relatively low customer activity in my datasets between 6 and 16 transactions per year, I expand the observation time segments to quarters for all datasets.

The definition of category breadth follows the firms' own definitions. In the case of the retailer datasets, the category comprises departments (e.g., men's apparel, children's apparel, and sport hard goods). Because the airline company only offers one category of product (flights), cross-buying in this context is often defined as the purchase of products from partner companies (i.e., those associated with the airline's loyalty program, such as hotels or car rentals; Lemon and v. Wangenheim, 2008). In an ISP context, cross-selling can have two forms. For one, in a classical sense, the ISP can cross-sell additional services such as IPTV, security services, etc. Unfortunately, I do not dispose of data on the sales of these additional services and, therefore, take a different and more unconventional perspective on cross-selling in the internet domain. Following the same reasoning that in the airline context revenues with partner sales constitute cross-selling, it could also be argued that a purchase from partner companies via a paid link on the ISP's portal represents a cross-sell. The dataset of the hardware store and the telco do not include category information in a time-series format, therefore they are excluded from the cross-buying analysis.

Again, I apply a linear fixed-effects regression to absorb uncontrolled stable customer characteristics (Greene, 2008). As in my analysis of spending levels, I only consider active periods to separate cross-buying from changes in purchase frequency.

The linear fixed-effects regression is defined as follows:

$$cross_i(t') = \alpha_i + \beta_1 t' \quad (3.6)$$

where

- $cross_i(t')$ = number of categories that customer i purchased from at time t ,
- t' = time of observation after first purchase (aggregated in quarters),
- α_i = intercept of customer i , and
- β_1 = regression coefficient.

Since cross-buying is defined as number of categories purchased from, the resulting variable represents count data, for which the observations can take only non-negative integer values. While often these variables can be treated as continuous measures, this approach might lead to distorted results since count data does not strictly satisfy the assumed linearity of response and their distribution is often skewed (Greene, 2008). Thus, the error terms do not follow the assumed normal distribution. Therefore, in line with most other studies, I use linear fixed-effects regression as primary analysis for an easy interpretability of the results and additionally validate my findings with an in this context methodologically more sound fixed-effects negative binomial model for count data as secondary analysis.

Here I assume that the counted events have a negative binomial distribution for each customer at each point in time. Based on Cameron and Trivedi (1998) the model can be formulated as follows:

$$P(y_{it} = r) = \frac{\Gamma(\theta + r)}{\Gamma(\theta)\Gamma(r + 1)} \left(\frac{\lambda_{it}}{\lambda_{it} + \theta}\right)^r \left(\frac{\theta}{\lambda_{it} + \theta}\right)^\theta \quad (3.7)$$

where

λ_{it} = expected value of y_{it} ,

θ = overdispersion parameter, and

$\Gamma(\cdot)$ = gamma function.

Then a log-linear regression decomposition of the expected value is assumed

$$\log \lambda_{it} = \alpha_i + \beta x_{it} \quad (3.8)$$

where the α_i are treated as fixed effects.

This model cannot be estimated using conditional likelihood maximization because the total counts per person are not a complete sufficient test statistic (Allison, 2010). Instead I use the unconditional form of the model by including $n-1$ dummy variables for n individuals.

3.4 Empirical Findings

3.4.1 Overview

I report the key results of my analyses in Table 7 (parameter estimates for dummy variables are omitted for better readability but can be found in Appendix A.1). The outcomes of the research questions are summarized in Table 8. Figure 16 shows the development of the analyzed aspects of customer profitability over time for each dataset, where the values are indexed for better comparability.

In all regressions I test for the validity of the relevant key assumptions (see Table 9). I first test for autocorrelation of the error terms by means of the Durbin-Watson-test. All values are close to 2, hence indicating no autocorrelation (Durbin and Watson, 1950; Greene, 2008). Additionally, I test for normality of the residuals using the Kolmogorov–Smirnov test (K-S test) statistic and a visual inspection of the histogram. For many analyses, the K-S test shows a statistically significant deviation from the normal distribution. Since however the K-S test becomes extremely sensitive to even small deviations with increasing sample size, its validity for large samples such as the present ones is disputed (D’Agostino and Stephens, 1986, p. 406; Panneerselvam, 2004, p. 320). Therefore more emphasis is placed on the histogram which suggests acceptable fit with the normal distribution.

Table 7: Results from Regression Analysis (Cohort 1)

Aspect	Dataset	Mean*	β_1 (time)*	R²
<i>Churn Probability</i>				
	Airline	.097	.005**	.98
	Hardware	.036	.001**	.63
	Fashion Retailer	.012	.001**	.99
	General Retailer	.015	.003**	.86
	Telco	.034	.002**	.86
	ISP	.062	.002**	.68
<i>Interpurchase Times</i>				
	Airline	.413	.038**	.25
	Hardware	.230	.037**	.25
	Fashion Retailer	.774	.085**	.53
	General Retailer	.469	.113**	.54
	Telco	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
	ISP	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
<i>Spending Levels</i>				
	Airline	.958	-.014**	.61
	Hardware	.808	-.020**	.22
	Fashion Retailer	.813	-.029**	.19
	General Retailer	.770	-.030**	.21
	Telco	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
	ISP	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
<i>Overall Revenue</i>				
	Airline	1.997	-.025*	.62
	Hardware	2.264	-.060**	.17
	Fashion Retailer	1.052	-.050**	.43
	General Retailer	1.595	-.090**	.30
	Telco	261.403	-.119	.74
	ISP	49.807	-.295**	.37
<i>Cross-Buying</i>				
	Airline	1.152	.007**	.42
	Hardware	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
	Fashion Retailer	1.850	.061**	.43
	General Retailer	2.106	.014**	.53
	Telco	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
	ISP	1.155	.228**	.46

Note. * = normalized per quarter; *n/a* = not applicable; * = $p < .05$; ** = $p < .01$

Table 8: Summary of Results

Research Question		Airline	Hardware Store	Fashion Retailer	General Retailer	Telco	ISP
RQ _{1a}	Churn Probability	++	++	++	++	++	++
RQ _{1b}	Purchase Frequency	--	--	--	--	n/a	n/a
RQ _{1c}	Spending Levels	--	--	--	--	n/a	n/a
RQ _{1d}	Overall Revenue	-*	--	-- ¹	--	-	--
RQ _{1e}	Cross-Buying	++ ¹	n/a	++	++ ²	n/a	--

Note. + = increasing over time; - = decreasing over time; n/s = no significant trend; n/a = not applicable; * = $p < .05$; ** = $p < .01$; ¹ = significant only for one cohort; ² = conflicting findings in cohort 2

Table 9: Key Test Statistics

Analysis	Durbin-Watson Test						Kolmogorov-Smirnov Test					
	Airline	Hardware Store	Fashion Retailer	General Retailer	Telco	ISP	Airline	Hardware Store	Fashion Retailer	General Retailer	Telco	ISP
Churn Prob.	2.10	1.28	1.40	1.64	1.87	1.19	.16	.12	.15	.20	.16	.21
Interp. Times	2.21	1.85	2.44	2.38	n/a	n/a	.27*	.24	.13*	.14*	n/a	n/a
Spending Levels	2.16	2.02	2.16	2.21	n/a	n/a	.19*	.24	.15*	.20*	n/a	n/a
Overall Revenue	2.21	1.85	2.30	2.00	1.10	1.43	.27*	.24*	.15*	.25*	.30*	.25*
Cross-Buying	2.03	n/a	2.32	2.43	n/a	1.35	.29*	n/a	.09*	.10*	n/a	.25*

Note. n/a = not applicable; * = $p < .05$

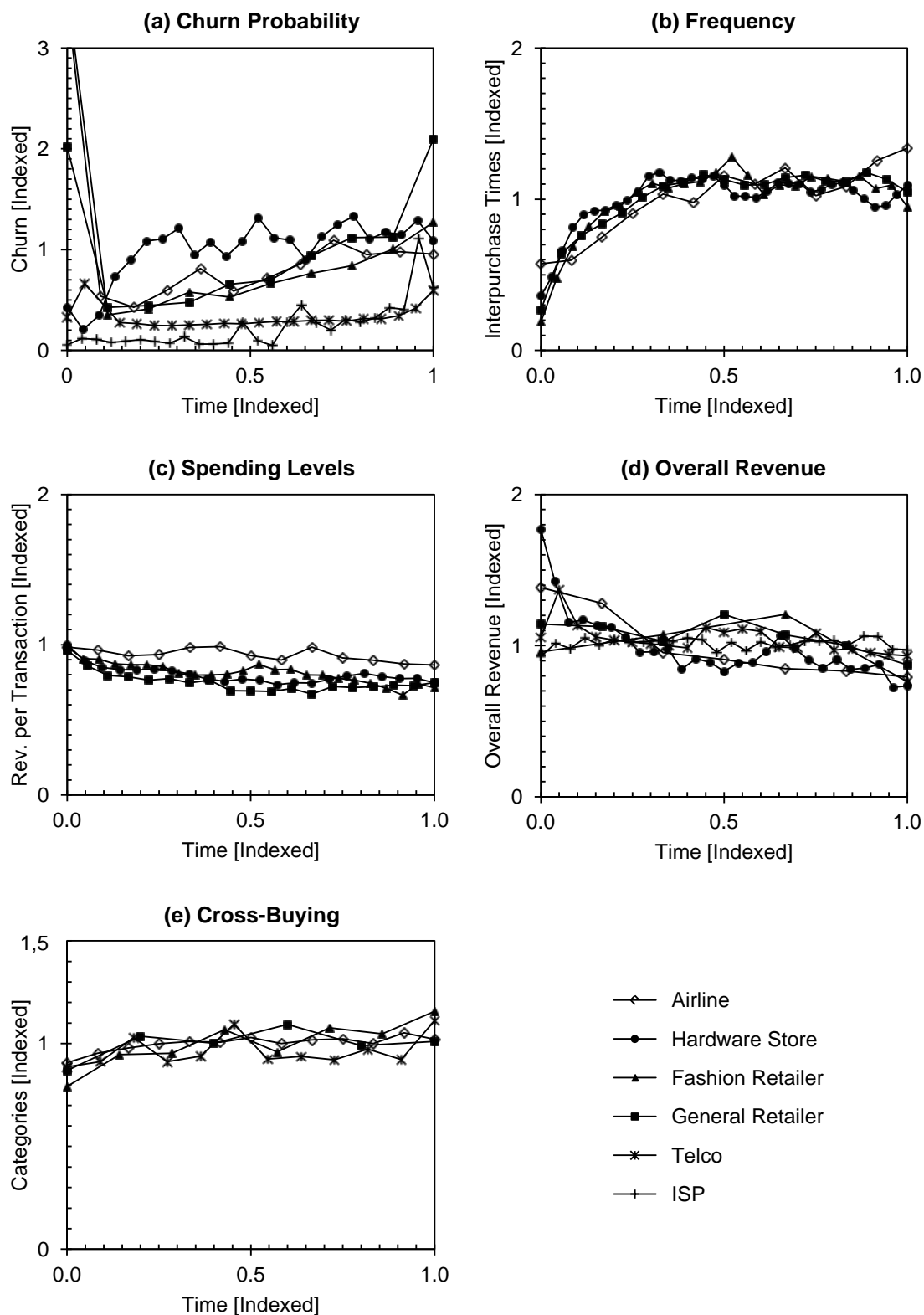


Figure 16: Behavioral Sources of Profitability over Time¹⁹
 Source: Own Illustration

¹⁹ Y-axes of graphs a, b, d, and e indexed by overall average; time-axes indexed by max. observed periods per dataset.

3.4.2 Churn Probability

Although previous studies' findings conflict, the prevailing tenet in customer relationship marketing is that churn decreases over time. My results show the opposite effect: in all datasets, the churn probability increases over the customer relationship duration. Some datasets in the non-contractual context show an initial peak in the first period, reflecting a large proportion of one-time buyers. Similarly for the telco dataset a slight peak exists after one year, representing contracts with respective minimum contract durations. Notwithstanding these artifacts that are adjusted for in the regression via dummy coefficients, churn probability generally increases with between .1 and .5 percentage points (~3% to 20%) per quarter.

It is important to note that this effect is only observable in a cohort-based analysis. In practice, managers often track churn only at the customer base level in which tenure-related effects are canceled out by the constant 'refreshment' with new customer acquisitions (Schweidel et al., 2006). Given this and because this study is the first to specifically document continuously increasing churn rates over a broad range of cross-industry datasets, these results in this unambiguosness mark very important findings and further highlight that the present tenet might be too undifferentiated.

3.4.3 Purchase Frequency

The tenet in customer relationship marketing expects purchase frequency to increase over time. My results contradict this notion: throughout all the (non-contractual) datasets, I consistently find that interpurchase times increase over time (i.e., transaction frequency decreases). On average with every quarter of customership, the interval between purchases increases by ~3 to ~10 days (~9% to ~24%). This trend seems especially steep in the first year of customer relationship duration, though it eventually flattens out. Further analysis on this particular development shows two interesting observations.

First, this trend seems to be at least partly due to an artifact from averaging purchase frequencies for the graphical representation. Table 10 shows a

comparison of the linear slope of this decrease of short-life vs. long-life customers using a median split on customership lengths and the correlation of overall customership length with this slope. As can be seen, the longer a customer stays with the company, the more gradual this slope is. Therefore, as short-life customers with high purchase frequencies churn, the average purchase frequency decreases. It is to note that this artifact only affects the graphical representation since fixed effects regression analyzes the trend deaveraged on a per customer basis. However, regardless, of the customership length, second, the purchase distribution of both short- and long-life customers resembles a Pareto effect where the bulk of the purchases take place at the beginning of the customership (see Figure 17). Both observations indicate a wear-out of the customers' demand. This is in line with Reinartz and Kumar's (2003) argument that high purchase frequencies are not sustainable because such customers stock up on items.

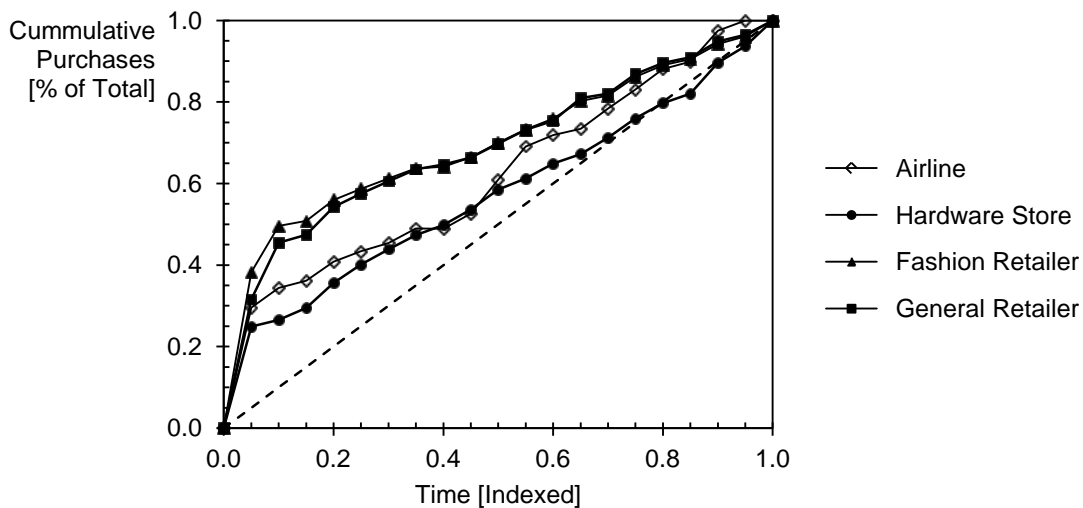


Figure 17: Cumulative Purchases as Share of Total Purchases over Time²⁰
Source: Own Illustration

²⁰ Only customers with observed churn event (i.e. known lifetime duration) considered.

Table 10: Comparison of Average Slope of Purchase Frequency of Short- and Long-Lifetime Customers

Dataset	Avg. Slope Coefficient		Correlation
	Short Lifetime	Long Lifetime	
Airline	.119	.083	-.83
Hardware Store	.185	.116	-.89
Fashion Retailer	.381	.264	-.76
General Retailer	.368	.185	-.94

3.4.4 Spending Levels

Throughout all the (non-contractual) datasets, I find decreasing spending levels over the customer relationship duration. Especially in the first periods, I find a strong decline that eventually flattens out. Overall, this decrease is comparably small with between ~1% to ~4%. Nevertheless, this finding contradicts the notion that more loyal customers are willing to pay higher prices, though it is consistent with the informal experience of practitioners. These results are particularly important because they reflect the pure development of customers' spending levels without side effects from general trends in prices (e.g., increasing fuel surcharges in the airline case, seasonal differences for the retailers).

3.4.5 Overall Revenue

As all non-contractual datasets show decreasing purchase frequency and spending levels, consequently I also find the overall revenues to decrease in these datasets. The average revenue per customer decreases by ~2% to ~6% per quarter, statistically significant for all non-contractual datasets²¹.

For the contractual context, the picture is less clear. In principle, also both contractual datasets exhibit the same trend. However since, here, revenues are at least to some extent predetermined by the contract (e.g., due to base fees) this

²¹ Although the results for the second cohort of the fashion retailer are not statistically significant

development is less pronounced and statistically significant only for the ISP dataset.

3.4.6 Cross-Buying

In line with existing research (see Table 3), I expected customers' cross-buying to be positively correlated with their relationship tenure because a broader purchasing behavior reflects a stronger relationship and familiarity with the firm's offerings. The analyses generally confirm this contention but with some caveats. The analysis of the primary cohort consistently shows increasing purchasing breadth: customers on average adopt between $\sim.01$ and $\sim.06$ additional categories per quarter ($\sim 1\%$ to $\sim 3\%$); or, in the case of the ISP, make $.23$ more clicks on paid links per quarter ($\sim 20\%$). For the general merchandise retailer, the analysis of the secondary cohort shows, however, a decreasing trend (at the $.05$ significance level).

In the light of these partly conflicting findings, the alternative and methodically more sound negative binomial regression model for count data becomes particularly important (see Table 11). The results generally support the original notion of increasing cross-buying. For the general merchandise retailer, the results still indicate decreasing category breadth in the secondary cohort (see Appendix A.1), however, not statistically significant. For the hardware store and the telco, I could conduct neither of the cross-buying analyses, because, for these datasets, I did not have category data as a time series.

Empirical evidence on the developmental trend of cross-buying over time is scarce (Reinartz and V. Kumar, 2003). Therefore, my results, which in general support the original contention of increasing cross-buying over customership tenure, represent an important contribution towards generalization.

Table 11: Results from NBD Regression Analysis

Dataset	Time	LL	DF	Pearson χ^2
Airline	.0021*	-4,089	3,405	.29
Hardware Store	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
Fashion Retailer	.0334**	-7,895	11,413	.53
General Retailer	.0072**	-4,332	11,895	.57
Telco	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
ISP	.4614**	-13,154	18,828	.66

Note. LL = Log-Likelihood; DF = degrees of freedom; *n/a* = not available;
 * = $p < .05$; ** = $p < .01$

3.5 Discussion

3.5.1 Summary of Findings

My aim was to investigate whether the customers' behavioral sources of profitability (i.e., churn probability, purchase frequency, spending level, cross-buying, and overall revenues respectively) change in the course of their customer relationship duration, and if so, whether this trend has a positive or negative effect. Though there is the tenet of increasing customer profitability, in my meta-analysis I showed that many studies on customer profitability over time show conflicting findings. Against this background, my findings provide an impulse to review the existing tenet more differentiated: for the three main exchange parameters—churn probability, purchase frequency, and spending levels—the results across all six datasets are remarkably consistent, indicating decreasing customer activity over time. Only my finding that customers over time increasingly purchase products from different categories is in line with the prevailing notion. Even as purchase frequency and spending levels decrease, customers seem to broaden their purchase behavior and increasingly buy products from other product categories. Taken together, this leads to my finding of decreasing revenues over time, contradicting the prevailing tenet of an increase of customer profitability. This trend is, however, less distinct in the contractual

contexts because, here, customer revenues at least to some extent predetermined by the contract.

Though my results by themselves are very consistent, when contrasted with previous findings the conflicting picture remains. Table 12 compares the findings on the trend of the behavioral aspects of customer profitability of previous research and this study with respect to number of datasets. The fact that this study is the first and only to investigate all behavioral antecedents comprehensively probably grants a high degree of expressiveness. However, for many aspects there exists a considerable amount of conflicting findings and, in particular, none of these aspects passes the threshold for generalization (compare section 2.5.3.2). In this regard, the strongest case can be made for an increasing churn probability which falls short of the requirement of consistency of findings and cross-buying which has not yet been analyzed by three independent authors. Therefore, the conclusion from this synthesis is that the development of the behavioral antecedents of customer profitability is context specific.

Table 12: Comparison of Findings of Previous Research and this Study with Respect to Number of Datasets and Studies

	Churn	Overall Revenues	Frequency	Spending Levels	Cross-Buying
<i>Previous Research</i> ²²					
Datasets with increasing trend	4 (4)	4 (1)	4 (1)	9 (4)	1 (1)
Datasets with decreasing trend	1 (1)	- (-)	3 (3)	1 (1)	- (-)
<i>This Study</i>					
Datasets with increasing trend	6 (1)	- (-)	- (-)	- (-)	4 (1)
Datasets with decreasing trend	- (-)	4 (1)	4 (1)	4 (1)	- (-)
<i>Overall</i>					
Datasets with increasing trend	10 (5)	4 (1)	4 (1)	9 (4)	5 (2)
Datasets with decreasing trend	1 (1)	4 (1)	7 (4)	5 (2)	- (-)

Note. Number of studies in parentheses; only significant first order effects considered

²² Based on studies and sources from Table 3.

3.5.2 Theoretical Contributions

This study as a review of generally held contentions on the trend of the development of customer profitability over time has more of a descriptive rather than theoretical focus. Nevertheless, I believe that my findings are relevant for the marketing domain also on a theoretical level and contribute to general theory underlying relationship marketing at least fourfold.

Most importantly and first, my results show that the present tenet of increasing customer profitability over the course of the relationship duration is a gross oversimplification. At the very least, this trend is context specific. Based on my discussion of relevant theories, I showed that many theories and concepts provide arguments both for and against relational market behavior of consumers (compare section 2.4.8). Thus, while most researchers so far have concentrated on concepts and market conditions in favor of a relationship orientation of consumers, a key implication of my work should be that it reemphasizes the existence and importance of both relational and transactional 'drivers'.

Following this notion of transactional and relational drivers, second, my results motivate the assumption that the balance between these drivers changes over time in favor of a transactions orientation of consumers. In particular, it adds support to (1) risk theory's proposition that as customers become more experienced over the course of the relationship, they become more comfortable in exercising their alternative options (compare section 2.4.5); (2) learning theory's variety seeking, i.e., the observation that after a certain familiarization, customers increasingly try new offerings to offset their boredom (compare section 2.4.4); (3) social exchange theory's expectancy for reciprocation which predicts that customers increasingly react with avoidance if their relational engagement is not reciprocated by the firm (e.g., due the anonymity of consumers or the limited interaction between the consumers and the firm; compare section 2.4.7); and (4) the notion based on learning theory that consumers over time learn about the firm's offering, which leads to a more focused buying according to their actual needs and enables them to better appraise the products based on solid reference prices (compare sections 2.4.4 and 3.2.3).

And third, researchers citing these theories usually implicitly assume that the setting of the exchange exhibits conditions that these theories explain. At this, my findings add support to arguments stating that due to the nature of competition, the anonymity of consumers, the limited interaction between the consumers and the firm, and the increasing standardization and commoditization of products and purchasing processes many of these assumptions do not hold in consumer markets (Christy et al., 1996; O'Malley and Tynan, 2000). Moreover, many arguments for increasing loyalty implicitly assume the customer's dedication to the relationship. However, my findings reemphasize that a customer's continuance of the relationship should not be confused with dedication, but could just as well be devoid of attitudinal loyalty and, e.g., be due to a momentary lack of alternatives. Furthermore, my findings also add support to the assumption that many of these conditions—at least in the consumer's perception—change over the course of the relationship as the consumer gains experience leading to an increasing transactions orientation (Bruhn, 2002, p. 22).

Above all and fourth, my findings highlight basic considerations based on the customer and industry life cycle (compare section 2.5.2): it is sheer implausible that customers or their need for a given type of product is immortal. At some point in time even the most loyal customers will cease their need for a product and terminate the relationship, resulting in an increase of churn rates (Li, 1995). Also many industries in the maturity and decline stage witness increasing price competition (Grant, 2005). Since the attractiveness of alternatives determine the strength of the firm-buyer relationship (Morgan and Hunt, 1994) as the price competition increases, the probability that customers will respond to this competitive pull and switch to a competitor who offers a comparable product for a cheaper price should, too, increase.

3.5.3 Managerial Implications

Despite conflicting results in academic research, the notion that customers become more profitable over time has 'silently' been promoted to a generalized directive in many marketing functions (CQ Transcriptions LLC, 2010a; b; c). In particular, Reichheld and Sasser's (1990) illustration of how additional profits from ever increasing purchase frequency, spending levels, price premium,

referrals and reduced cost of servicing the consumer over time add up to a multiple of the initial base profits is ubiquitous. My dissertation shows that this reasoning, which is still fixed in many marketing managers' minds, is at the very least a gross oversimplification and needs to be overthrown. Throughout all datasets, I find increasing churn rates and decreasing purchase frequency, spending levels and, respectively, overall revenues. These findings reveal that overall customer activity attenuates indicating a decreasing trend in customer profitability. Thus, marketing managers need to reassess their customer relationship marketing strategy. High investments in the beginning of a customer relationship duration that renders a customer initially unprofitable cannot be categorically justified with later increasing profits.

Acknowledging that these trends are at least context specific, marketing departments must continuously probe the dynamics in their domain and develop strategies to counter possible detrimental tendencies in customers' exchange relational behavior. Only if companies base their allocation of scarce marketing resources on a realistic view of the development of customer profitability they can render their marketing spending more efficient. Above all, my findings reemphasize the importance of customer acquisition. With decreasing profitability of existing customers, companies need to put more focus on acquiring new customers to balance possible detrimental developments in their customer base.

In addition to practice, my findings should influence academic teachings in the first place. Marketing knowledge is to a great, if not its most important part, disseminated through textbooks. Many textbooks that I reviewed explicitly or implicitly indicate that central customer relationship exchange parameters (e.g., retention, purchase frequency, spending) typically increase over time. Therefore, a central implication of my results is that textbooks should be corrected to take a less optimistic view of customer relationship development over time.

My findings are also relevant beyond the pure marketing domain. For an outside-in perspective on a company (e.g., in the course of company valuation), its customer equity cannot be determined by extrapolating (or even increasing) customer profits, but rather must be adjusted for possible decreasing trends in the behavioral sources of profitability. Valuations that are willfully based on the

prevailing belief that customers at least maintain their profitability over time will systematically overestimate the value of their targets.

Finally, my findings should motivate a shift in perspective throughout many corporate functions. In particular, if pricing managers find a decreasing trend in customer revenues they might consider fostering tariff structures that stabilize these revenues. In this context, flat-rates seem to be a promising approach, the application of which will be discussed in the following chapters.

3.5.4 Limitations and Further Research

In this analysis, I specifically excluded cost and focused only on the revenue part of customer profitability. Though if cost could be tracked precisely and comprehensively, its inclusion would render my analysis more comprehensive, previous research suggests that the inclusion of cost would not affect the results (Reinartz and V. Kumar, 2000a, 2002). Thus, other than the fixed cost digression of customer acquisition cost, there is no reason to believe that the cost of servicing a customer changes significantly over time. In the extreme, one could even argue that the inclusion of cost into the analysis would be detrimental to generalizability because of its company specificity. The cost a company incurs in servicing a customer depends highly on its internal processes and structures. Additionally it is often very dependent on internal cost accounting practices (Yadev and Berry, 1996).

Among other things, my findings stress that additional research needs to be done to generalize statements on the development of customer profitability and its behavioral sources. To my knowledge, this study represents the largest in terms of datasets, but a broader empirical analysis is still necessary. Acknowledging contrasting findings of other studies in different contexts, further research could address these differences across industries and try to identify causative factors, why the development of customer profitability is positive or negative in certain contexts. If these factors are manipulable by the firm, this understanding might help marketers to develop actions to invert negative trends and strategies to foster a positive development. As a first step in this direction, a further decomposition of the behavioral sources of profitability would be valuable: For example, can

increasing or decreasing churn rates be lead back to whether the customer has switched companies or completely renounced the respective offerings?

Finally, my work has a descriptive focus. While I already highlighted several indicative theoretical contributions that can be drawn from my findings in section 3.5.2, more research needs to be done on a theoretical level. This seems to be even more important as my results reemphasize the big gap between conceptual and factual knowledge (compare section 2.5.4). As discussed in section 2.4.8, many of the existing economic and behavioral theories to explain relationship orientation of consumers conflict. However, most of these theories so far have been applied only from a static perspective. In this regard, my findings could motivate, e.g., a life cycle based examination.

4 Flat-Rate Pricing as Strategy to Stabilize Customer Revenues

4.1 Introduction

Flat-rates as tariffs where customers pay only a fixed fee allowing the possibility to consume as much as possible are becoming increasingly popular. Although most common in telecommunications, today, flat-rates can be found in virtually all industries—from utilities, vacations, restaurants to public transportation. For customers, this unlimited consumption at a fixed price can be a bargain and seems to have a big appeal (Della Vigna and Malmendier, 2006; Lambrecht and Skiera, 2006; Nunes, 2000). From the company perspective, flat-rates are not without risk, because their possibility of unlimited consumption at a fixed price can induce heavy usage and, hence, possibly making flat-rates unprofitable for the company. Therefore, the provision of these tariffs is traditionally economically motivated by low or no marginal costs, high overcapacities or disproportionate cost of measuring the actual usage (Yadev and Berry, 1996; v. Wangenheim and Freudenschuß, 2008).

First companies, especially in the telecommunications industry, have however started to motivate flat-rate tariffs with a different reasoning. In line with my findings from the previous chapter, this industry is reporting decreasing customer revenues since several years due to price erosion and fixed-mobile- and voice-data substitution which can only in part be absorbed with new or additional services. Here, several companies have started to adopt flat-rate pricing as a strategy to stabilize consumer revenues (Dellis, 2009; TF Investext, 2010; Thomson Reuters, 2005). Against the background of a decreasing revenue trend, flat-rate at first sight may seem like a win-win situation. However, informal experience from practitioners and recent research shows that the balance act of making flat-rate tariffs profitable and satisfactory for customers in the long run is not trivial (Oi,

1971; Yadev and Berry, 1996; v. Wangenheim and Freudenschuß, 2008). In particular with regard to customer satisfaction, flat-rates have an interesting property: recent studies (Della Vigna and Malmendier, 2006; Lambrecht and Skiera, 2006; Nunes, 2000) find that consumers show flat-rate tariff preferences (the so-called *flat-rate bias*), which may lead them to choose a flat-rate tariff even though pay-per-use would lead to lower bills. On the one hand, this effect offers a revenue upside potential for companies but, on the other hand, represents a price premium that might redound to dissatisfaction on the customer side.

The next two chapters are dedicated to investigating this double bind of flat-rates between additional profit due to flat-rate bias and its potentially detrimental effect on customer loyalty. To provide a thorough theoretical grounding this chapter will first introduce and discuss relevant research background on flat-rate pricing and, especially, flat-rate bias. The next chapter will then empirically investigate the consequences of flat-rate bias.

4.2 Price Discrimination with Optional Tariff Structures

4.2.1 Rationale of Price Discrimination

Pricing is one of the most important aspects in marketing, because of its direct influence on consumers' purchase decisions and the firm's profitability as well as its strategic position (T. J. Smith, 2011, p. 3). In reality, we observe only rarely a single price or even price structure for a good or service. This strategy of differential prices represents a form of price discrimination (M. Armstrong, 1999).

In general, price discrimination describes a pricing technique where sellers charge different prices for the same²³ goods or services to different consumers with the purpose to capture the market's consumer surplus without losing purchases (Phlips, 1983, p. 6). As Figure 18a shows, with a single clearing price the seller, first, misses the part of the consumers with a lower reservation price and, second,

²³ It is to note, that the definition of price discrimination is not undisputed, i.e., with regard to what 'the same' means (Phlips 1983, p. 6).

sells to customers who are prepared to pay higher prices. Often, these pricing schemes pay tribute to Gossen's first law of diminishing marginal utility (Gossen, 1854, p. 45) and set decreasing marginal prices with increasing volume (see Figure 18b).

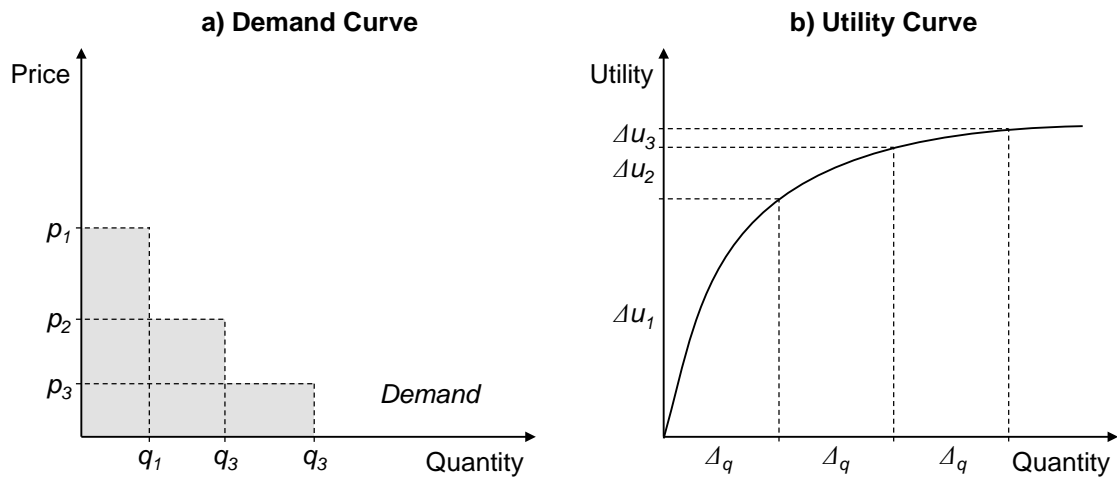


Figure 18: Exemplary Demand and Utility Curve

Source: Own Illustration

However, in order for price discrimination to be possible, the seller must be able to separate markets according to consumer demand to avoid arbitrage. If the seller cannot manage to keep the markets or market segments separate, a secondary market will be created, where buyers in the lower-prices market will resell to buyers in the higher-prices markets; hence creating competition for himself. For this reason, price discrimination works better for services than for physical goods, since services cannot be stored and resold (Phlips, 1983, p. 14; Vargo and Lusch, 2004). Because price discrimination cannot happen in a perfectly competitive industry in equilibrium, it is usually termed monopoly price discrimination in economic jargon. Besides the non-transferability of the good or service, the separation can however also be achieved by impeding transferability of demand. Sellers for example attach special trademarks, brands, or packaging size to increase qualitative differences and ensure that customers with a high reservation price do not switch to the cheaper segments (Phlips, 1983, p. 15).

4.2.2 Taxonomy and Microeconomics of Price Discrimination

According to the seminal analysis by Pigou (1920, p. 279), three types of price discrimination can be distinguished: in *first degree price discrimination*, the seller charges a different price for each consumer. Because, if successful, the seller captures the full consumer surplus, this type of price discrimination is also called 'perfect discrimination'. Though Pigou (1920, p. 280) states that this type is only of academic interest since the seller would have to dispose of perfect information about the consumers' willingness to pay, it does occur in some, albeit imperfect forms such as in auctions or bazaar bargaining. With *second degree price discrimination*, the seller differentiates his offering into a menu of offerings at different prices. Due to the seller's incomplete information, the menu is offered to all buyers who then self-select their offering based on preference. In contrast to this self-selection, in *third degree price discrimination*, the seller separates the buyers into different groups and charges different prices based on their different demand elasticities. Basis for this market segmentation can be a personal, spatial, or temporal differentiation.

With optional tariff structures, sellers typically offer a menu of price plans which customers themselves can select from. Hence, they represent price discrimination of the second degree. Within this menu, the prices are differentiated primarily according to the usage amount. While in theory a continuous pricing structure offers the greatest flexibility, for reasons of transparency, simplicity, and thus acceptancy, in practice typically pricing structures consisting of between one and three pricing elements are used (Lambrecht et al., 2007; Philips, 1983, p. 166). The microeconomics of common tariff structures of these three types are depicted in Figure 19. As can be seen, under optional tariffs the usage price and demand are related by a demand function that is conditional on the user's tariff choice (Train et al., 1987). Therefore, the price has a direct effect on usage as well as an indirect effect via tariff choice.

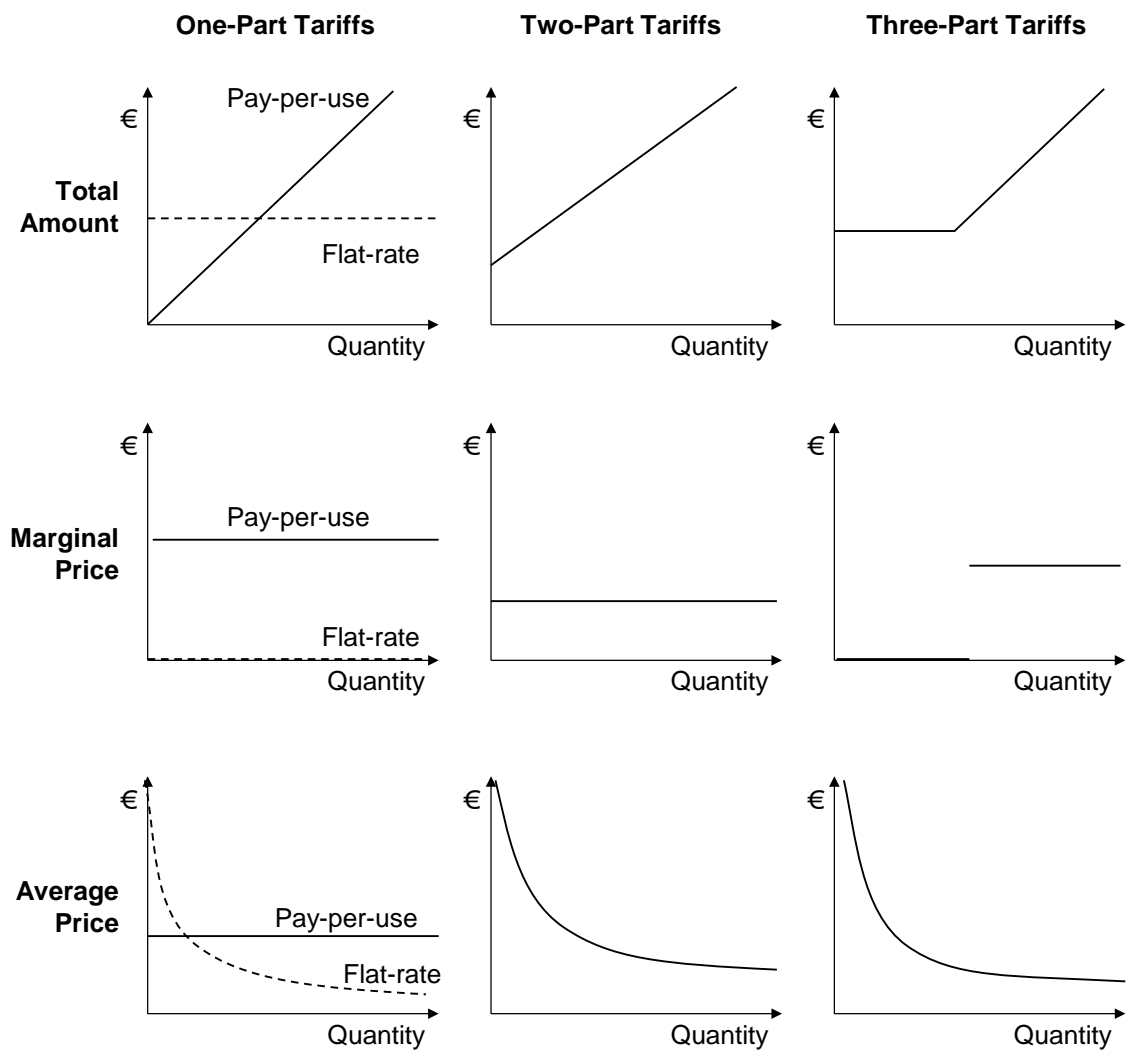


Figure 19: Micro-Economics of One-, Two-, and Three-Part Tariffs

Source: Own Illustration

One-part tariffs have only one pricing element. Though strictly speaking no price discrimination, the most prominent example is a pure pay-per-use tariff, where consumers are charged a specific amount of money for every unit of consumption. Because the marginal price is constant, these tariffs are also called 'linear tariffs'. Linear tariffs are widespread for classical services and goods: concert tickets, handymen, gas, or groceries, and so on are typically charged at a constant rate per unit of consumption.

In contrast to this usage-dependency, flat-rate or all-inclusive tariffs are another very prominent tariff structure. Here, consumers pay a fixed fee regardless of their actual usage, i.e., allowing for limitless consumption. While linear tariffs are

becoming increasingly uncommon in many industries, flat-rates catch on as the prevalent pricing scheme, especially in contexts where measuring the actual usage of a consumer is costly or with only small or no marginal costs, such as telecommunications, public transportation, or sports clubs (Sundararajan, 2004). This is because otherwise an average price per usage approaching zero could result in low or even negative profits for the seller. On the other hand, however, flat-rates offer the opportunity for the seller to exploit the buyer's demand uncertainty by the temporal separation of choice and usage. Hence, despite of this profit risk, they are also increasingly found in other contexts²⁴, such as mobility guarantees and gas flat-rates for cars or all-you-can-eat buffets.

Two-part tariffs are one of the earliest price structures examined in modern economics (T. J. Smith, 2011). The total invoice amount typically consists of a usage independent base fee plus a metered price. From a price political view, both price components can contain profit potential, but in practice one price component frequently subsidizes the other. In general, base fees are positive, though sometimes also negative base fees exist. These tariffs price discriminate in the sense of Gossen's first law since, with increasing usage, the average price per unit decreases and eventually approaches the marginal price. Hence, the consumer can 'select' his price via his usage. Two-part tariffs are commonly used in telecommunications services and the utility sector.

Three-part tariffs are very similar to two-part tariffs, except that they usually offer an inclusive usage allowance per period. The marginal price only applies to usage in excess of the allowance, where the tariff 'behaves' like a two-part tariff. Within the allowance, it is like a flat-rate tariff. Due to this duality of three-part tariffs, they are often not considered as a separate tariff type but subsumed as a flat-rate under one-part tariffs (Heidenreich and Handrich, 2010). Accordingly, the seller can also exploit the buyer's demand uncertainty and profits from the temporal separation of consumer choice and usage, since the buyer commits to a specific volume at front but only later decides on the number of units per period to consume (Lambrecht et al., 2007). These tariffs are mostly found in the

²⁴ Though oftentimes with a 'fair flat constraint', i.e., the limitation of the usage at a certain 'reasonable' threshold.

telecommunications industry, with mobile telephony and internet access tariffs being the most prominent examples.

4.3 Theoretical Aspects of Tariff Choice with Optional Tariffs

4.3.1 Rationality in Tariff Choice

Standard economic theory assumes that a consumer will pick the tariff that maximizes his expected consumer surplus (S. J. Brown and Sibley, 1986). Or stated differently: consumers will choose the tariff that minimizes their cost given the expected usage. Since the usage is not known in advance, this assessment always involves uncertainty and, thus, risk. For studying choices among risky prospects, expected utility theory is considered "the major paradigm in decision making since the Second World War" (Schoemaker, 1982, p. 529). It assumes the consumer to choose between alternatives in a way that maximizes his expected utility, i.e., the alternative i with probability p_i so that $p_i \cdot u(i)$ is maximized (Swalm, 1966). His preferences can be described by a well defined utility function $u: \star \rightarrow \mathbb{R}$ assigning ordinal numbers to the alternatives. In order to represent a decision-maker's choice by the maximization of expected utility, the utility function is required to satisfy a set of properties such as completeness, transitivity, independence, and continuity (v. Neumann and Morgenstern, 1944).

All of these axioms are logically correct. Yet, the model only describes how individuals from a rational point of view should behave (prescriptive or normative)—and not how they actually do behave (descriptive). Based on our everyday experience, we know that individuals show systematic violations of rationality in their choice behavior (Allais and Hagen, 1979; Allais, 1953)²⁵.

²⁵ The most prominent violation of the expected utility theory is known as the "Allais Paradox", where respondents were given the following two questions. Decision 1: Choose between (A) an 80% chance of \$4,000; (B) \$3,000 for sure. Decision 2: Choose between (C) a 20% chance of \$4,000; (D) a 25% chance of \$3,000. Most respondents chose (A) over (B) in the first decision and (D) over (C) in the second decision, which is a violation of expected utility theory's substitution axiom according to which in this setting a decision-maker should prefer A over B if and only if he prefers C to D (C. R. Fox and Poldrack, 2008).

Especially under uncertainty, human decision-making is only intentionally rational and in practice subject to bounded rationality and influenced by several psychological factors. As a result, consumers often show a preference for tariffs that do not lead to the minimum invoice amount and, thus, do not follow the above rationality assumption. This cognitive mistake is called *tariff bias*.

Until the end of 1970, this irrational behavior was believed to be too chaotic and unsuited for modeling. At this, prospect theory which is discussed in the next section provided a major breakaway because it explicitly incorporated irrational behavior in an empirically well supported manner. Consequently it was the first rational approach to model irrational behavior (Wakker, 2010, p. 2).

4.3.2 Prospect Theory

Based on the aforementioned critique of expected utility theory in its application as a descriptive model of decision-making under risk, the psychologists Kahneman and Tversky (1979) developed an alternative model, which they called *prospect theory*. Prospect theory bases on the two elementary observations that individuals (1) in general discard aspects that are shared by all prospects under consideration; and (2), given the same probability associated with two outcomes of an event, they weight the positive outcomes differently than negative outcomes. Founding on these observations, the theory describes the decision process in two stages.

In the first phase—the *editing phase*—all possible outcomes of the decision are analyzed and undergo a subjective transformation. In particular, individuals decide which outcomes they see as basically identical and set a reference point to which all alternatives are compared. Lower outcomes are considered as losses; higher outcomes as gains. The shift in emphasis from final wealth to change from the reference point is in line with the human perceptual process, which tends to notice changes or differences more than absolute magnitude or resting states (McDermott, 1998, p. 27). This tendency can also lead to inconsistent preferences when the same choice is presented or *framed* in different forms. This is because framing of prospects influences the perceived reference point. One example on

how to influence the reference point is to describe the outcome of prospects in terms of their losses as compared to their gains. This has been shown e.g., in the domain of medical treatments, where decisions differ depending on whether possible outcomes are described in terms of survival or mortality rates (McNeil et al., 1982).

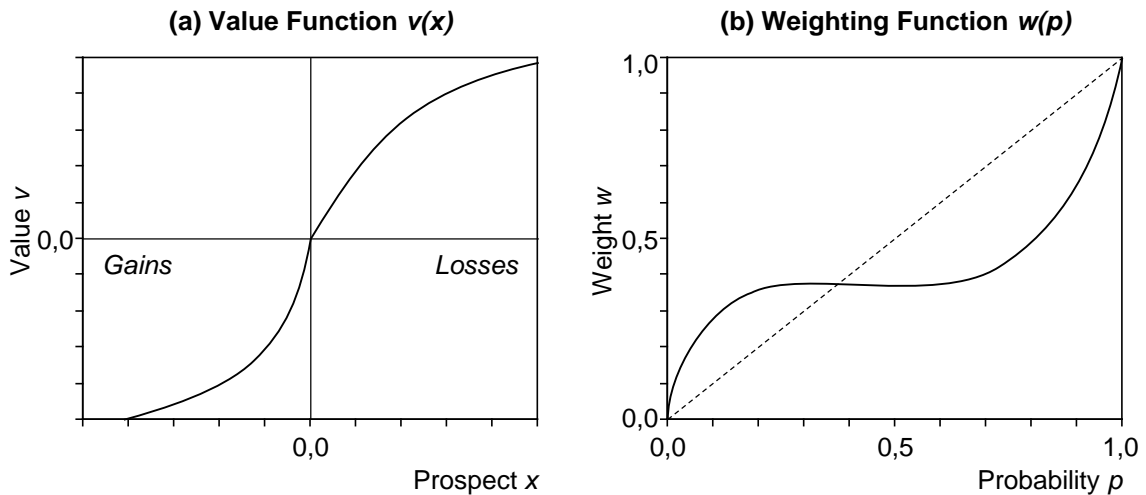


Figure 20: Shape of Value and Weighting Function

Source: Own Illustration based on C. R. Fox and Poldrack (2008, p. 149)

In a second phase—the *evaluation phase*—the decision-maker evaluates the edited alternatives based on the attractiveness of the outcomes and an assessment of their respective probabilities. In discrimination to the rationality axioms of expected utility theory, this evaluation specifically incorporates a psychophysical and therefore potentially non-rational transformation of outcomes and probabilities. The value V of a prospect x with probability p_x is given by

$$V(x, p_x) = v(x)w(p_x) \quad (4.1)$$

based on a value function $v: \star \rightarrow \mathbb{R}$ that rates the attractiveness of the outcome; and on a weighting function $w: [0; 1] \rightarrow [0; 1]$ that represents the impact of the respective probability on the valuation of the prospect (C. R. Fox and Poldrack, 2008, p. 149).

The value function is characterized by two elementary cognitive artifacts, as depicted in Figure 20a: First, the attractiveness of outcomes is rated with decreasing marginal utility, both for negative and positive outcomes. That is,

individuals are more sensitive to deviations close to the reference point. This reflects a common observation in practice: the difference between 10 Euro and 20 Euro appears larger than between 1.000 Euro and 1.010 Euro. And second, the value function is steeper in the loss area than in the gain area, i.e., $v(x) < -v(-x)$. This implies a so-called *loss aversion*, i.e., the observation that people tend to underweight gains compared to losses (Tversky and Kahneman, 1991).

The second component of the evaluation phase is the weighting function $w(\star)$. It weights the value of an outcome not by its probability but assigns a decision weight describing the impact of the probability on the valuation of the respective alternative. Though decision weights do not correspond directly to traditional notions of probability, they are normalized so that $w(0) = 0$ and $w(1) = 1$. Similar to the value function, also the weighting function captures diminishing sensitivity to changes in probability with increasing distance from impossibility or certainty in an inverse S-shaped form as depicted in Figure 20b. This accounts for the observation that individuals are more sensitive to differences in probability near impossibility and certainty than in the intermediate range of the probability scale. And hence that events, which are perceived to be unlikely or absolutely certain have more or respectively less impact in the decision-making process than they normatively should²⁶ (C. R. Fox and Poldrack, 2008, p. 150). This tendency, called the *certainty effect*, contributes to *risk aversion* in choices involving sure gains and to *risk seeking* in choices involving sure losses (Kahneman and Tversky, 1979).

Hence, prospect theory's value differs from neoclassical utility in two main properties: First, whereas utility is necessarily linear in the probabilities, value is not. Second, whilst utility is dependent on final wealth, value is defined in terms of gains and losses, i.e., deviations from current wealth.

²⁶ For example, Tversky and Kahneman (1992) found in a study that, overall, participants were indifferent between receiving a lottery ticket offering 1% chance at \$200 and receiving \$10 for sure and were also indifferent between a ticket with 99% chance at \$200 or receiving \$188 for sure. Thus, whereas the first and the last hundredth of probability are valued at \$10 and \$12 respectively, the intermediate 98 hundredths are valued only about \$1.80 per hundredth.

4.3.3 Mental Accounting

Based on the value function of prospect theory, Thaler (1985) derived the theory of mental accounting. It describes analogously to financial accounting how individuals organize, evaluate, and keep track of financial activities in decision-making, especially with regard to multiple outcomes. As implied by the preceding metaphor, in this theory individuals are assumed to have an implicit accounting system with virtual accounts that represent symbolic linkages between specific acts of consumption and payments. While the evaluation of accounts where gain and loss coincide is straightforward, Thaler hypothesized in his hedonic editing hypothesis that for temporally separated gains and losses people try to code outcomes to achieve the most pleasant outcome possible. In particular, individuals try to integrate multiple outcomes when an integrated evaluation yields higher value than a separate evaluation, $v(x_1 + x_2) > v(x_1) + v(x_2)$; and try to segregate them when segregation yields higher value, $v(x_1 + x_2) < v(x_1) + v(x_2)$. However, Thaler later limited this hypothesis and stated that "there must be some limits to our abilities to engage in self-deception" (Thaler, 1999, p. 187).

Thaler originally assumed a temporal invariance in his theory, i.e., that past losses have a constant effect in the evaluation. Subsequent research has shown, however, that the temporal separation of losses and gains has significant impact on consumers' evaluations. Though individuals' irrational attention to sunk cost (Arkes and Blumer, 1985; Thaler, 1980, 1985) was confirmed, Gourville and Soman (1998) for example found the *sunk cost effect* to be less pronounced if losses significantly precede gains. Particularly to account for observations that indicate high relevance of the sequence, temporal distance, and reciprocal interactions of payment and consumption, Prelec and Loewenstein (1998) further evolved Thaler's original theory to a *double-entry theory of mental accounting*.

Double-entry mental accounting assumes that a purchase always entails two entries, where one entry records the "net utility derived from consumption after subtracting the disutility of associated payments", and the other "records the net disutility of payments after subtracting the utility of associated payments" (Prelec and Loewenstein, 1998, p. 8). Three assumptions describe how these reciprocal hedonic interactions of the pain of payments and pleasure of consumption are experienced. First, while pending payments are fully recognized, past ones are

largely written off (*prospective accounting*). Additionally, the pain of payments made prior to consumption is blunted by thoughts of consumption. Hence, under prospective accounting, the experience of consumption and payment is enhanced by prepayment—an observation that they label *debt aversion*. In particular, they note that "individuals can enjoy consumption that has already been paid for as if it were for free" (Prelec and Loewenstein, 1998, p. 4). This is consistent with what Gourville and Soman (1998) label as *payment depreciation effect*, i.e., the observation that consumers gradually adapt to a historic cost with the passage of time.

The second assumption is that individuals allocate future payments to future consumption or allocate future consumption to future payments (*prorating*). In other words, individuals try to match future consumption to future payments.

Finally, the third assumption is that individuals do not always fully link payments and consumption (*coupling*). Loewenstein and Prelec suggest that the degree to which payments attenuate the pleasure of consumption and consumption buffers the pain of payments varies across situations, payment methods, and individuals.

4.3.4 Attribution Theory

Attribution theory provides important insights to understand customers' attitudes and behavior in post tariff choice situations. It can be traced back to work of Heider (1958) and Weiner and colleagues (E. E. Jones et al., 1972; Weiner, 1985) who have further developed Heider's work to a theoretical framework that has become a major research paradigm of social psychology. The basic premise of attribution theory is what Heider (1958, p. 4) calls "naive psychology" or "common sense psychology", i.e., that people are trying to make sense of the social world by trying to arrive at causal explanations for events. Attribution theory addresses the issue of how people attribute these causes, in particular by distinguishing between internal and external attribution. Heider defines *internal attribution* as an individual's inference that the cause of a behavior lies within the person himself, i.e., his character traits, ability, personality, mood, efforts, attitudes, or disposition. *External attribution* is given if the individual arrives at the conclusion that the behavior is due to situative factors such as the task itself, other people, or luck.

The three main phenomena commonly observed that are important in the context of tariff choice are the *actor-observer bias*, the *fundamental attribution error*, and the *self-serving bias*. The actor-observer bias refers to the observation that the perceived cause of an event follows from the particular perspective of the explainer. The person carrying out a particular act has the tendency to explain his own behavior with external circumstances, whereas an uninvolved observer tends to attribute the causes for the act in question to internal characteristics (E. E. Jones and Nisbett, 1971). The fundamental attribution error describes the bias on part of an observer tending to stress internal factors to a greater extent than situational factors when explaining behavior of others (E. E. Jones and Harris, 1967). And the self-serving bias is a common pattern where individuals make more internal attributions for their positive outcomes and more external attributions for their failures (Riess et al., 1981; Snyder et al., 1976; Zuckerman, 1979).

4.4 Flat-Rate Bias in Optional Tariff Structures

4.4.1 Definition, Existence, and Extent of Flat-Rate Bias

As stated, when choosing among several tariffs, irrationality of human decision-making can cause the user to make economically suboptimal choices (Lambrecht et al., 2007). This tariff bias is particularly common for flat-rates where it is confirmed by several studies in various contexts (see Table 13). According to Train (1991, p. 211) a flat-rate bias is defined as a situation in which consumers “value flat-rate service over measured service even when the bill that the consumer would receive under the two services [...] would be the same”.

The occurrence of flat-rate bias is an important phenomenon for companies offering flat-rate tariffs. According to Lambrecht and Skiera (2006a), flat-rate bias can lead to profit increases of up to 182%. The extent of flat-rate bias, nevertheless, varies across studies and industries with respect to both prevalence and amount of monetary loss. Mitchell and Vogelsang (1991) for example find that 45% of households in their study pay too much for telephone plans with inclusive allowance. In a survey of health club users, Nunes (2000) finds 61% of customers overpay on average 38%. And for internet services, Lambrecht and Skiera (2006)

find 38% of customers to exhibit a flat-rate bias, of which more than half paid at least 100% more than they would have in the economically best tariff.

Table 13: Flat-Rate Bias Literature Overview (Uhrich et al., 2011)

Authors	Dataset	Key Results
<i>Existence of Flat-Rate Bias in Usage Data</i>		
Train et al., 1987	Telephone usage data of 2,963 households	Existence of flat-rate bias
Hobson and Spady, 1988	Telephone usage data of 172 households	Existence of flat-rate bias
Train et al., 1989	Telephone usage data of 520 households	Existence of flat-rate bias
Kling and van der Ploeg, 1990	Telephone usage data of 1,456 households	Existence of flat-rate bias
<i>Degree of Flat-Rate Bias in Usage Data</i>		
Mitchell and Vogelsang, 1991	Telephone usage data of 151,000 households	Many consumers choose add-on packages without using it (45%)
Kridel et al., 1993	Telephone usage data of 2,786 households	76% of flat-rate customers pay too much
Nunes, 2000	Survey among 129 health club users	61% of flat-rate customers pay too much (would have saved on average 38% with pay-per-use)
Miravete, 2002	Telephone usage data of 1,542 households	6–12% of flat-rate customers pay too much
Della Vigna and Malmendier, 2006	Gym usage data of 7,978 customers	On average, customers with annual contracts pay \$700 excess compared with pay-per-use
Lambrecht and Skiera, 2006	Usage data of 10,882 ISP customers	38% of flat-rate customers pay too much
<i>Flat-Rate Bias in Tariff Choice Experiments</i>		
Prelec and Loewenstein, 1998	Survey among 89 airport visitors for four services	52% of respondents prefer flat-rate
Nunes, 2000	Survey among 120 students regarding a swimming pool	35-93% of respondents prefer flat-rates
Nunes, 2000	Survey among 100 grocery shoppers (online supermarket)	87% of respondents prefer flat-rate
Lambrecht and Skiera, 2006	Survey among 241 students	18–95% of respondents prefer flat-rate (at same price level)

According to Lambrecht and Skiera (2006), the motivational and cognitive explanations for a flat-rate bias can be grouped into four distinct causes: the insurance, taxi-meter, convenience and overestimation effect. The following section will discuss these in detail.

4.4.2 Causes of Flat-Rate Bias

4.4.2.1 Insurance Effect

The *insurance effect* describes the tendency of consumers to avoid financial losses due to the risk of overusage or demand variability. Accordingly, consumers give up the opportunity to pay less with a variable pricing scheme and instead fix their invoice amount with a flat-rate tariff to avoid paying more.

The insurance effect can be explained with three theories: risk aversion, loss aversion, and option value. Risk-averse behavior emerges when people prefer a flat-rate because they fear the uncertainty that they might pay more (Miravete 2002; Nunes 2000; Train 1991). Risk-averse customers are willing to pay a premium for a determined outcome even if the statistically expected outcome is lower. Applied to tariff choice situations, risk-averse customers prefer a fixed monthly fee over variable pricing in order to exclude the risk of paying more.

Since for a wrong tariff choice the potential loss is typically rather small compared to the income of the consumer and to the cost of the 'flat-rate insurance', several authors question risk aversion as sole explanation (Clay et al., 1992; Miravete, 2002; Mitchell and Vogelsang, 1991). Especially for small amounts, prospect theory's loss aversion can serve as a good explanatory approach (compare section 4.3.2). Consumers evaluate losses and gains relative to a reference point. In the context of tariff choice, customers could fall for framing effects and set the flat-rate price as reference point due to intensive communication of this price point. But even if customers remain unaffected by framing effects and set their statistically expected invoice amount as the reference point, customers would still prefer the constant invoice amount of the flat-rate due to the greater steepness of the value function. With pay-per-use pricing, the bill amount fluctuates around this expected value. Though arithmetically interim losses and gains balance in the

long term, indexed by the value function the negative values of the losses outweigh the positive values of the gains (Lambrecht and Skiera, 2006).

Finally, some authors also argue that there is an option value of the flat-rate (Kridel et al., 1993; Lambrecht and Skiera, 2006). In theoretical literature, an option value describes "the value of an option to use a resource (or service) in an uncertain world, where the uncertainty can involve preferences, income, prices, and/or supply" (Kridel et al., 1993, p. 129). Hence, the consumer's option to consume the service in future more than originally planned at the same price represents additional value.

4.4.2.2 Taximeter Effect

Consumers are said to exhibit a *taxi-meter effect* when they do not want to 'hear' the taximeter ticking as they use the service. It reminds them of the pain of paying and lowers their consumption enjoyment (Lambrecht and Skiera, 2006). The taxi-meter effect can be lead back to mental accounting theory as discussed previously (compare section 4.3.3): with a variable pricing scheme the costs are not known ex ante but incur through the usage of the service. Hence, the link between cost and usage is very salient, which leaves little room for hedonic editing. In this situation according to mental accounting theory, gains and losses are evaluated jointly. Thus the pain of payment lowers the perceived benefits (though the coupling assumption allows for imperfect imputation of cost and gains). Or worse: if the post-payment character of the tariff dominates the user's conception, the incurred cost are perceived as debt, leading to a big hedonic plunge after consumption, when the user has only the payments to look forward to (Prelec and Loewenstein, 1998).

In contrast a flat-rate pricing scheme nurtures the users' prepayment preference (Heidenreich and Handrich, 2010; Lambrecht and Skiera, 2006). In line with prospective accounting, the accrument of the cost at the beginning of the period regardless of the actual usage, for one, leads to a depreciation of the payment. And, for another, it diminishes the sum of residual payments and, thus, increases net enjoyment. The gains of consumption can then be evaluated segregated from

the losses and, hence, users can enjoy the consumption as if it were for free (Prelec and Loewenstein, 1998).

4.4.2.3 Convenience Effect

While the previous two effects can be led back to irrationality of individuals, the *convenience effect* still exists under rational decision-making. A rational decision between different tariff alternatives requires the user to calculate and compare expected invoice amounts with the respective tariffs given his estimated usage pattern. A convenience effect occurs when the consumer chooses a flat-rate tariff to avoid this cognitive effort. Especially when many alternatives are available, customers tend to make the easiest choice. This can be the most common tariff, a promoted tariff, or the one with the easiest pricing structure (Heidenreich and Handrich, 2010; Lambrecht and Skiera, 2006).

From a transaction cost theory perspective, the convenience effect can be attributed to search cost of tariff choice (Nunes, 2000; Winer, 2005, p. 32). Especially given today's plethora and complexity of available tariff structures, gathering detailed information about available tariffs and their pricing schemes produces high external search cost for the user. To this end, flat-rates are significantly less 'expensive' since the required information comprises only one figure: the fee for unlimited usage. Likewise, flat-rates with their simplistic tariff structure also save the user on internal search cost otherwise necessary: understanding the structure of pay-per-use tariffs, determining the projected costs based on the expected usage behavior, and comparing the projected costs of potential tariffs requires significant mental effort.

4.4.2.4 Overestimation Effect

An *overestimation effect* occurs if consumers base their decision for a flat-rate tariff on an exaggerated estimate of their usage. This exaggerated estimate can arise due to the consumer's limited experience and consequently uncertainty or wishful thinking. If users lack sufficient experience with a service, they are susceptible to misjudgments of their usage. In particular, advertisement campaigns portraying

intensive service usage can foster the users' overestimation of their own service usage (Mitchell and Vogelsang, 1991). Similarly, when confronted with several tariff plans, consumers often rely on salient but insufficient characteristics or cues to determine their own expected usage level. This is also in line with Parducci's range-frequency model which predicts that consumers tend to use available categories or levels for judgment equally often (Parducci, 1965). Since any usage has a natural minimum of zero, the number of possible outcomes below a realistic expected value is limited and in particular lower than the amount of possible outcomes above this realistic expected value. As a result, individuals typically perceive a higher likelihood of consuming more than of consuming less (Nunes, 2000).

The observation that individuals rely on the number of possible states that lead to an outcome as a proxy for the probability of that outcome is also shared by Nunes (2000). Nunes showed that when deciding between alternative tariffs, users frequently rely on a simple heuristic that bases on extreme values in usage volatility rather than on rational, statistical values such as average usage or standard deviation. This heuristic which can be approximated by the *ratio rule* can induce an overestimation of their usage. According to the ratio rule, the perceived probability of overusage is dependent on the extent that the maximum (q_{max}) and minimum (q_{min}) imaginable usage levels differ from the break-even usage (q_{be}), i.e., where both alternative tariffs yield the same invoice amount. The larger the upper range ($q_{max} - q_{be}$) compared to the lower range ($q_{be} - q_{min}$), the higher the perceived likelihood of overusage compared to the likelihood of underusage:

$$Ratio = \frac{q_{max} - q_{be}}{q_{be} - q_{min}} \quad (4.2)$$

Nunes empirically validated this ratio rule. He showed that though people do not consciously follow the formula, they act as if they did. Or in other words: consumers who perceive maximum and minimum usage as particularly high are more likely to choose a flat-rate even if their average usage would not justify it (Lambrecht and Skiera, 2006). However, in this instance, the boundary between overestimation and insurance effect is somewhat blurred, since a larger range of possible outcomes also acts on the users' demand for insurance.

But even if customers have experience with the service, they sometimes intentionally overestimate their future usage, simply because they want their usage to increase due to wishful thinking (Einhorn and Hogarth, 1986). This precommitment by paying upfront for unlimited usage as incentive for increased usage is especially the case if the consequences of using the service are desirable (Wertenbroch, 1998). A typical branch that profits from this effect are health clubs, where users are over-confident in their discipline and subscribe to annual or sometimes even bi-annual contracts even though pay-per-use would have been significantly cheaper given their actual usage pattern (Della Vigna and Malmendier, 2006)

4.4.3 Consequences of Flat-Rate Bias

As discussed these four flat-rate bias effects can cause customers to significantly overpay with flat-rates. At first sight, this seems like a desirable effect for firms that seem to benefit from constant revenues at a higher level than with pay-per-use. The question is however: can this be sustainable? If customers become aware of paying too much with their flat-rate, economic theory predicts that they will change to a cheaper alternative (Khan et al., 2004). This can be achieved either by switching the tariff within the service provider or by churning to a competitor. Thus, service providers face this risk of negative consequences of flat-rate bias on customer loyalty. They must decide, e.g., to migrate those endangered customers to pay-per-use before they potentially churn to a competitor, or to not react and benefit from higher revenues.

Despite this high managerial relevance, research on this question is still scarce. So far only one study investigating the consequences of flat-rate bias on customer loyalty exists (Lambrecht and Skiera, 2006). Based on three months transactional data of 10,882 DSL customers, Lambrecht and Skiera identify customers with flat-rate bias using two criteria. The less strict criterion 'overall' attests flat-rate bias if a customer would have saved money in sum over all three months. The stricter criterion 'always' requires savings from switching to pay-per-use in every single month. When using the 'overall' criterion, they do not observe any impact of flat-rate bias on switching and churn. Only under the stricter criterion 'always' does the analysis show increased tariff switching (10% significance level), but still no

impact on churn. Thus their conclusion is that customers are "paying too much and being happy about it" (Lambrecht and Skiera, 2006, p. 212).

Based on these results, the authors also estimate the impact of flat-rate bias on the company's profits. As they did not find negative impact of flat-rate bias on customer lifetime, they find customers with flat-rate bias to have a substantially higher customer lifetime value than customers in least costly tariffs. This would imply no need for action for managers regarding flat-rate bias but rather suggest fostering of flat-rate bias.

This finding is however in contrast with general research on tariff choice, which shows that in general customers who have chosen the economically right tariff have higher retention rates than customers who have chosen the wrong tariff. Joo, Jun, and Kim (2002a) for example analyze a sample of 10,000 mobile telecommunications customers. They find those customers who subscribe to the wrong calling plan to show significantly lower retention rates than those who subscribe to the economically right plan. Analyzing the impact on customer profits, they observe that for about half of the customers with a wrong tariff these negative implications on customer loyalty exceed short-term profit increases. Thus, their recommendation is that these customers should be encouraged to switch to the optimal calling plans. Wong (2010) obtains similar results when investigating 1,403 postpaid mobile telecommunications customers. And similarly, Iyengar (2004) shows that the access fee affects consumer churn more than the marginal price. These findings are supported by attribution theory predicting that customers attribute the failure of the wrong tariff choice to the provider and, as a consequence, lose loyalty and eventually churn (compare section 4.3.4).

4.4.4 Necessity for Further Research

Customers' overpayment due to flat-rate bias is an important source for the profitability of flat-rate tariffs. At the same time, customer loyalty is a key concern of managers and marketing managers in particular (S. Gupta et al., 2004; Reichheld and Sasser, 1990; Reichheld, 2003). Therefore, the question whether flat-rate bias is sustainable and a real win-win situation for customers and firms is of high relevance. Against this background, it is even more surprising that the

fundamental question of whether, or whether not, flat-rate bias comes at the price of customer lifetime has received so little attention.

Given the conflicts with findings from general research on tariff choice, the findings of Lambrecht and Skiera (2006) are astonishing and deserve a closer inspection. Though they in principle find that customers react to their overpayment, they only find this to realize in tariff switching rather than churn. However, their analysis is based on a relatively short observation window of three months. Assuming that a customer needs at least two months to recognize his flat-rate bias (one month of overpaying could be regarded as an exception) and another month or two for the cancellation (often, contract cancellation requires some notification period), the churn event likely occurs beyond their observation window and is hence unobserved. Their research also does not follow a longitudinal cohort-based approach, which appears especially important for studying customer defection rates (Reinartz and V. Kumar, 2000b).

The shortcomings of existing research together with contradictory findings highlight the need for further research. In the following chapter, I will further investigate consequences of flat-rate bias on long term customer profitability.

5 Empirical Investigation of Flat-Rate Bias Consequences²⁷

5.1 Introduction

The last chapter gave an introduction to tariff structures and flat-rate pricing in particular. I argued that flat-rates in deed may represent a suitable strategy to stabilize declining customer revenues but also pointed out the need for further research on the question whether this can be sustainable. Therefore, this chapter re-investigates the sustainability of flat-rate bias. Does flat-rate bias increase tariff switching and customer churn (RQ₂), and in an effort to resolve contradicting evidence: is the market position of the service provider a moderator of flat-rate bias consequences (i.e., the type of consequences; RQ₃)?

In what follows I will first develop concrete hypotheses. I will answer them with two independent empirical studies that I will describe in the subsequent sections with respect to research methodology and findings.

5.2 Hypothesis Development

5.2.1 Impact of Flat-Rate Bias on Tariff-Switching

Following economic theory, customers are rationally acting individuals who strive to maximize their financial benefits (S. J. Brown and Sibley, 1986; compare 4.3.1). They therefore should choose the tariff that minimizes their expected costs and maximizes their expected utility. However, utility depends on assumed future

²⁷ This chapter is based on the joint paper of Felix Frank, Fabian Uhrich, Florian v. Wangenheim, and Jan Schuman with the title: "When Doing Nothing is Dangerous".

usage behavior, so tariff choice is a decision made under uncertainty. In these cases, human decision-making often is rational only by intention. In practice, decisions often turn out to be economically incorrect, in that they violate rational choice theory (Allais 1953; compare 4.3.1). When customers realize that their assumptions are wrong, they should—following economic theory—switch their tariff to the appropriate plan at least in the long-term (Khan et al., 2004). Thus, similar to Lambrecht and Skiera (2006), I expect:

H_{1a} Customers with a flat-rate bias have higher tariff-switching rates than customers without a flat-rate bias.

Behavioral decision researchers also argue that consumer decision making is not solely rational but also affected by emotional aspects (Andersson and Engelberg, 2006; compare section 4.3). The taxi-meter effect, for example, increases customer experience and happiness during consumption (Lambrecht and Skiera, 2006). Fun, enjoyment, and happiness are a basic consumption goal sought after when using services (Batra and Ahtola, 1991; O'Curry and Strahilevitz, 2001). In addition to achieving the utilitarian and functional benefits, consumers often also strive for hedonic, experiential gratification at the same time (Voss et al., 2003). Thus, the taxi-meter effect increases service consumption benefits and may justify higher costs. The insurance effect also provides additional benefits—a feeling of being safe from bill shocks which lets customers enjoy consumption more because they do not need to worry about varying or unexpectedly high costs.

Depending on the consumer's individual appraisal of these psychological benefits, both the taximeter and insurance effect flat-rate bias effects may justify the higher costs of a flat-rate until certain degrees. But with increasing monetary losses due to a flat-rate bias, the balance may shift, taking into account one-time switching costs as well (T. A. Burnham et al., 2003) will be exceeded. Accordingly I hypothesize as follows:

H_{1b}: The higher the monetary losses that customers experience from flat-rate bias, the more likely they are to switch tariffs.

5.2.2 Impact of Flat-Rate Bias on Churn

A situation in which consumers become aware of paying too much with their flat-rate is very likely to trigger a broader price search (Xia et al., 2004). In this search, they might not only compare prices within their current service provider, but might also look around for what competitors can offer. For example, in the telecommunications industry prices are changing rapidly and there might be cheaper competitive offers in the market alluring customers. Therefore, besides the risk of tariff switching there is also a risk of churn.

Following attribution theory (compare section 4.3.4), individuals tend to attribute positive, successful outcomes to themselves personally while they rather attribute negative outcomes to external/ situational factors (self-serving bias). In the context of a customer who has just realized that he is paying too much with his flat-rate, this should lead to external attribution (C. Peterson et al., 1982; Riess et al., 1981): The customer attributes the poor tariff choice to the service provider. Even worse, consumers are likely to attribute this wrong choice to internal characteristics of service provider (fundamental attribution error), assuming deceptive pricing which finally leads to negative feelings towards that service provider (Wong, 2010a). Similarly could also be argued with social exchange theory (compare section 2.4.7) because his in this situation disappointed expectancy of reciprocity of relational engagement would leave the consumer unsatisfied with the relationship (Yi and Gong, 2009). As a result, the customer might not only consider switching the tariff, but also churning away from the current service provider.

H_{2a}: Customers with flat-rate bias have higher churn rates than customers without flat-rate bias.

Also in the context of churn, I suspect that the psychological value of the taximeter and the insurance effects might absorb some negative consequences of flat-rate bias if the monetary loss is rather low. Accordingly, I suspect these effects to become particularly important if the monetary loss due to flat-rate bias is low. Furthermore, pricing or savings potential respectively is the key reason for a customer to switch to competitors (Joo et al., 2002). Therefore I postulate:

H_{2b}: The higher the monetary loss that customers experience due to flat-rate bias, the more likely they are to churn away from their service provider.

5.2.3 Impact of the Competitive Position on the Consequences of Flat-Rate Bias

As was highlighted in section 4.4.4, considerable conflicts regarding the concrete consequences of flat-rate bias exist between the findings of Lambrecht and Skiera (2006a) and other general research on the impact of tariff choice on customer loyalty (Joo et al., 2002; Wong, 2010a). One explanation could be found in the competitive position of the firm which has a significant influence on marketing (Burns, 1986; Hooley et al., 2008) and many other corporate functions (Dess and P. S. Davis, 1984; Hill, 1988; A. I. Murray, 1988). Michael Porter (1980a) differentiates two generic business-level strategies: differentiation or cost leadership²⁸.

A differentiation strategy aims at offering services with unique qualities, such as high speed, reliability, or a unique customer experience. Premium service providers often promote their unique quality and outstanding service, so they can be regarded as followers of a differentiation strategy (Choi et al., 2001). Such a strategy allows the provider to charge higher prices than the industry average (Dess and P. S. Davis, 1984) which attracts customers with low price sensitivity (Hill, 1988; A. I. Murray, 1988). A cost leadership strategy instead aims at offering services at the lowest price in the market, or at least at the lowest price-to-value ratio (Porter, 1980). Low-cost service providers implement a cost leadership strategy (Choi et al., 2001) and attract customers who are very price aware and price sensitive (Hill, 1988; A. I. Murray, 1988).

Price sensitivity also drives consumer behavior in terms of price search, such that "higher price sensitivity implies that consumers attach greater importance to discovering lower prices and hence will exhibit higher search propensity" (Mehta et al., 2003, p. 69). In addition to the higher price search propensity, customers

²⁸ I intentionally leave out his third, the so-called 'focus strategy', as there are controversial discussions in academia regarding its value add. I follow the notion that it can be seen as a special case of one of the former two (A. I. Murray, 1988; Porter, 1985).

with high price sensitivity tend to be less loyal (Santonen, 2007). They thus should be more likely to discover the existence of flat-rate bias and, once they recognized that they pay too much, are less loyal and more likely to react (switching or churn). In contrast, the lower price sensitivity of premium service provider customers implies that they have a lower price search propensity and thus a lower likelihood of discovering their flat-rate bias. Finally, the sophisticated relationship marketing employed by premium service providers likely lowers price sensitivity and further increases loyalty among their customers (Grönroos, 1994).

Therefore, I expect:

H₃: Low-cost service provider customers exhibit greater reactivity (switching and/or churning) to flat-rate bias than do premium service provider customers.

Once customers discover that they are paying too much with their flat-rate and they decide to correct their economically suboptimal tariff choice, the question becomes *how* they eventually react (switching or churning). As the attractiveness of alternative offers on the market determines the strength of a customer-firm relationship, it is a driver of customer loyalty (Morgan and Hunt, 1994). For customers of premium service providers with high price levels, competitive offers from the average or low-cost market segment are likely to be very attractive from a financial perspective. They provide higher expected savings, which implies a higher risk of churn. For low-cost provider customers though, prices are already very low, as should be the comparative attractiveness of alternative offers. Hyper-competition puts additional pressure on the low-cost segment. Cost advantages erode quickly, leading to very small price differences among the competitors within their segment (D'Aveni, 1994). Thus the achievable savings from competitive offers are greater for premium service provider customers than for low-cost service provider customers. Therefore I expect following traditional economic theory:

H₄: Premium service provider customers exhibit higher risk of churn than do low-cost service provider customers in response to flat-rate bias.

5.2.4 Synthesis

In the last sections I developed several hypotheses on the consequences of flat-rate bias in general and the amount of monetary loss due to flat-rate bias in particular as well as differences in the respective reactivity and the 'direction' of the reaction with regard to the competitive position of the firm. Combining these hypotheses, I come to the conceptual research model shown in Figure 21.

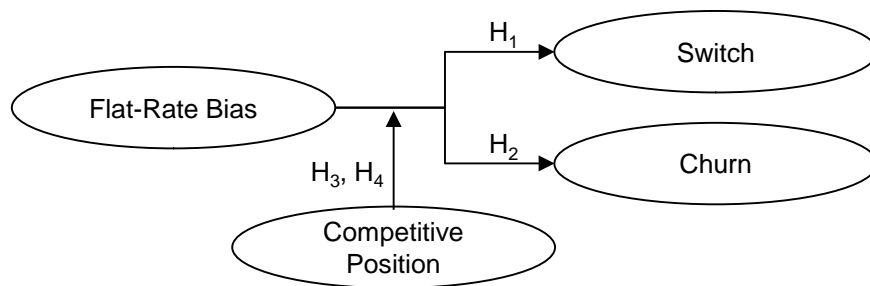


Figure 21: Synthesized Conceptual Research Model
Source: Own Illustration

5.3 Transactional Study

5.3.1 Research Design

5.3.1.1 Research Context and Data

To address the first two hypotheses I examine the transactional and invoice data from the German ISP already used in section 3.3.1. Again I use a cohort based approach and track 21.490²⁹ customers who signed up with the ISP in the first quarter of my observation window over a two years period on a monthly basis. I only included customers in the sample that chose between four of the ISP's major tariffs: (1) no fixed fee but a high usage price, charged per minute; (2) a medium fixed fee for a monthly time allowance and a lower usage price per minute for excess minutes; (3) a medium fixed fee for a monthly volume allowance, with a medium usage price per additional megabyte; and (4) a high fixed fee for unlimited access. Hence I have two time-based and two volume-based tariffs; the

²⁹ 3.377 customers with special tariffs were excluded from the analysis.

price differences between the respective small and large tariffs are comparable (Euro 16.95 vs. Euro 20.00). Customers can monitor their usage on the ISP's connection manager application. There is no minimum contract duration, thus customers can cancel or switch their contracts within a short timeframe. Basic descriptive information about the datasets is provided in Table 14.

Table 14: Basic Descriptive Information of Transactional Data

	Overall	Tariff 1	Tariff 2	Tariff 3	Tariff 4
Number of customers	21,490	5,628	3,289	2,077	10,496
Avg. customer age [years]	42.0 (δ 12.6)	43.5 (δ 13.1)	43.7 (δ 12.3)	42.7 (δ 12.6)	40.2 (δ 12.3)
Avg. usage vol. [GB]	6.1 (δ 16.2)	.1 (δ .3)	.2 (δ .7)	.5 (δ .8)	12.3 (δ 20.1)
Avg. usage time [h]	147.2 (δ 222.3)	6.5 (δ 12.6)	18.8 (δ 20.3)	72.0 (δ 136.5)	277.7 (δ 244.4)
Avg. invoice amount [Euro]	18.4 (δ 14.7)	7.5 (δ 18.5)	17.6 (δ 14.5)	11.7 (δ 18.1)	25.8 (δ .0)
Avg. observed periods [months]	17.9 (δ 6.3)	16.9 (δ 7.2)	17.9 (δ 6.3)	19.4 (δ 5.1)	17.9 (δ 6.3)

Note. δ = standard deviation; allocation of users to tariffs based on tariff in first period.

In chapter 3 I found a general decreasing trend of customer activity and overall revenues for customers in this data set. Under flat-rates' constant revenues one would consequently expect that this trend therefore translates in an increasing amount of monetary loss due to flat-rate bias. A fixed effects regression³⁰ of the amount of monetary loss due to flat-rate bias over time supports this notion and shows an increase of 0.0187 Euro per month ($R^2=0.54$; $p<0.01$). Figure 22 depicts the development graphically.

³⁰ The regression is specified as $frb_i(t) = \alpha_i + \beta_1 t$ where $frb_i(t)$ is the amount of monetary loss due to flat-rate bias of customer i in time t and α_i , β_1 , and t have the same meaning as in equation (3.6).

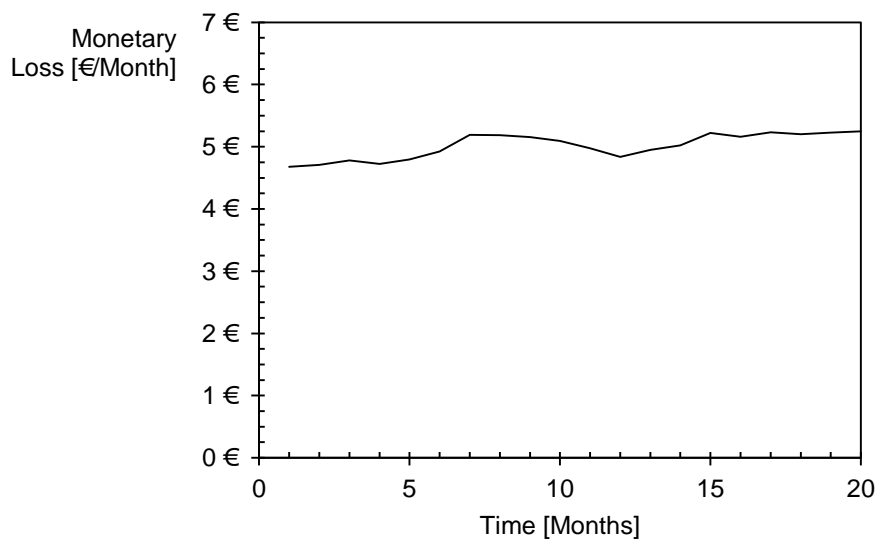


Figure 22: Development of Monetary Loss Due to Flat-Rate Bias over Time
Source: Own Illustration

5.3.1.2 Identification and Quantification of Flat-Rate Bias

Tariffs with inclusive allowances, strictly speaking, are two-part tariffs rather than flat-rate tariffs (compare section 4.2). Since however in the present case these allowances are considerably high and in line with other research (Heidenreich and Handrich, 2010; Lambrecht and Skiera, 2006) I treat these as flat-rate tariffs. Accordingly, I consider a user to exhibit a flat-rate bias if he has chosen the tariff with the higher inclusive allowance (hereafter FR-tariff) but given his usage the respective 'smaller' tariff (hereafter PPU-tariff) would have resulted in a lower total invoice amount. In line with Lambrecht and Skiera (2006) I use two criteria to determine if a user has a flat-rate bias over his (observed) lifetime: I consider the user to 'overall' exhibit a flat-rate bias if, in sum, the PPU-tariff would have been less expensive; and to 'always' exhibit a flat-rate bias if the PPU-tariff would have been the cheaper choice for every single month. The criterion 'always' thus is stricter and encompasses the 'overall' criterion.

In my analyses I quantify the actual amount of the flat-rate bias as the average monthly monetary loss incurred by a user due to his bias. To calculate this amount frb_u , I determine for every user u with a FR-tariff for each month t the hypothetical invoice amount $inv_{u,t}^{PPU}$ if he had chosen the PPU-tariff. If a user exhibits a flat-rate bias I define the resulting average monetary loss as the average

difference of the actual and hypothetical invoices where for users without a flat-rate bias this amount is set to zero:

$$frb_u = \begin{cases} \text{avg}_t(inv_{u,t}^{PPU} - inv_{u,t}^{FR}) & \text{if user exhibits FRB,} \\ 0 & \text{else.} \end{cases} \quad (5.1)$$

Table 15: Existence and Amount of Flat-Rate Bias

	PPU	FR
Number of customers	7,705	13,785
Avg. invoice amount per month	€ 8.6 (δ 18.4)	€ 23.9 (δ 7.9)
Bias criterion 'overall'		
Users with FRB	<i>n/a</i>	41.66 %
Avg. amount of FRB	<i>n/a</i>	€ 13.51 (δ 5.93)
Bias criterion 'always'		
Users with FRB	<i>n/a</i>	23.97%
Avg. amount of FRB	<i>n/a</i>	€ 16.26 (δ 2.76)

Note. *n/a* = not applicable; δ = standard deviation;

5.3.1.3 Consequences of Flat-Rate Bias on Tariff-Switching and Churn

I analyze two consequences of flat-rate bias. First, I investigate whether the fact that a user exhibits a flat-rate bias leads to higher tariff switching or churn probability (H_{1a} and H_{2a}). And second, I am interested whether this potential increase depends on the actual amount of the monetary loss incurred due to the flat-rate bias (H_{1b} and H_{2b}).

The first question can be answered using a very simple methodology. Typically churn and switching probabilities of users with and without flat-rate bias are compared by calculating the respective proportions $P(churn | FRB)$ and $P(churn | no FRB)$ of users churning within the observation window; and $P(switch | FRB)$ and $P(switch | no FRB)$ for switching and testing for significance of these differences (Heidenreich and Handrich, 2010; Lambrecht and Skiera, 2006). For this test, commonly the independent t-test as a parametric test is used (Greene, 2008); or if the respective assumptions such as normal distribution and

homogeneity of variances do not hold, the non-parametric counterpart of the t-test, the Mann–Whitney–Wilcoxon test. In fact especially for large samples the Mann–Whitney–Wilcoxon test is often recommended as default method due to its greater robustness and typically superior efficiency (Conover, 1999, p. 272; E. L. Lehmann, 2010, p. 176). I follow this recommendation in my analyses.

The latter question basically is a time to event study with a continuous predictor variable. This analysis is considerably more complex because it requires previously dichotomous parameters to be considered as continuous parameters. First, 'flat-rate bias' vs. 'no flat-rate bias' is differentiated as to the amount of monetary loss due to flat-rate bias; and second, 'has switched' vs. 'has not switched' or 'has churned' vs. 'has not churned', respectively, to after how much time did the event in question happen.

For this type of analysis scholars have used a variety of approaches. In the probably most prominent study on this subject matter, Lambrecht and Skiera (2006), for example, use a nested logistic regression model investigating the influence of the magnitude of flat-rate bias on the consumer's decision to change his tariff and, if so, whether to switch tariff or churn completely. In fact, the use of logistic regression for modeling churn probability seems to be the most commonly used approach (Neslin et al., 2006) and is widely propagated in literature from data mining (Buckinx et al., 2007; H. Hwang et al., 2004; Mozer et al., 2000) and CRM (Bolton et al., 2000; Rust et al., 2004). However especially in last two decades, a set of statistical methods from medical research called *survival analysis* is becoming increasingly popular (Bolton, 1998; Fader and Hardie, 2007; Li, 1995).

There exist strong arguments in favor of survival analysis. First, logistic regression can only handle dichotomous dependent variables hence these models ignore the actual time to the event by reducing to the general problem of binary classification: has the customer churned within the observation window or not. Especially in my context where there is no minimum contract duration, the customer is continuously evaluating his customership. Here, survival analysis uses duration data as a continuous parameter and differentiates whether a customer canceled the service in the second or in the 23rd month. In the former case one would assume a much higher propensity to churn. Therefore, ignoring this

information would reduce the precision of the estimates (Allison, 2010). As already briefly discussed in section 3.3.3.2, another advantage of survival analysis is its ability to handle censoring more effectively. Whereas with logistic regression, subjects with right censoring during the observation window would have to be discarded as incomplete observation, survival analysis can include these up to the point of censorship. This type of censoring can occur, e.g., in the case of the telecom operator, because the contract is suspended for an indefinite time or due to poor data quality.

Hosmer and Lemeshow (2000, p. 205) attribute the high popularity of logistic regression for these types of analysis mainly to its availability in many software packages and its ease of use and "no longer recommend that logistic regression analysis be used to approximate a time to event analysis". Fader and Hardie (2007, p. 84) even conclude that for churn studies, survival analysis "should be the first tool the researcher pulls out his toolkit". And Helsen and Schmittlein (1993, p. 397) find survival analysis to be superior to other methods such as logistic and least squares regressions "in terms of stability of the estimates, face validity of the parameter estimates, and predictive accuracy".

In general, survival analysis bases on modeling the subjects' hazard of an event—typically death—over time. The hazard rate at a specific duration time is the probability of this event conditioned that the event has not occurred until that time (see Appendix A.2 for an introduction to survival analysis). In the context of this study, the event under consideration is tariff switching or churning. Due to its simplicity, probably the most common hazard model is the Cox proportional hazard model. It can be specified in this context with the following hazard function:

$$h(t, frb) = h_0(t)e^{\beta_0 + \beta_1 frb}, \quad (5.2)$$

where

$h(t, frb)$ = hazard of a user with flat-rate bias frb at time t ,

t = time,

frb = amount of monetary loss due to flat-rate bias of a user,

$h_0(t)$ = (unspecified) baseline hazard function, and

β_0, β_1 = regression coefficients.

Because the Cox Proportional Hazard model does not specify the baseline hazard, it is a semi-parametric model³¹. However, the use of full parametric hazard models can be more efficient and provide more meaningful results (May and Hosmer, 1998). This is because (1) the estimation of the complete hazard function allows making inferences on the actual survival times or churn probabilities respectively. And (2), it accommodates a decomposed inspection of covariate specific effects and general trends over time (Hosmer et al., 2008, p. 244)

Therefore besides the Cox proportional hazard model, I also use full parametric specifications. I follow general recommendations to first employ several specifications—the Weibull, the exponential and the normal hazard model—in an exploratory analysis and test their appropriateness using a test statistic (Hosmer et al., 2008; Jamal and Bucklin, 2006; Kleinbaum and M. Klein, 2005). Specifically I use the Akaike Information Criterion (AIC) for the final model selection (Akaike, 1974, 1983; K. P. Burnham and D. R. Anderson, 2002, p. 75).

My findings in section 3.4.1 already suggest the use of the Weibull hazard function, which has already been found to match churn data in an ISP context (Jamal and Bucklin, 2006). A useful property of the Weibull specification comes from its shape parameter p which allows the baseline hazard to increase ($p < 1$), be constant ($p = 1$), or to decrease ($p > 1$) over time. Furthermore as an accelerated failure time model it is robust against the omitting of variables³² (Ghosh et al., 2011).

These full parametric models differ from the Cox proportional hazard model in that they specify the baseline hazard with concrete distributions. The respective definitions of $h_0(t)$ are given in Table 16 and plotted in Figure 23.

³¹ As is shown in Appendix A.2, when estimating the hazard ratio, the baseline hazard will cancel out since it is independent of the covariates if the hazards are proportional over time.

³² This however does not refer to the omitted variable bias, but to instabilities with regard to additional variables often observed with survival analysis (Ghosh et al., 2011).

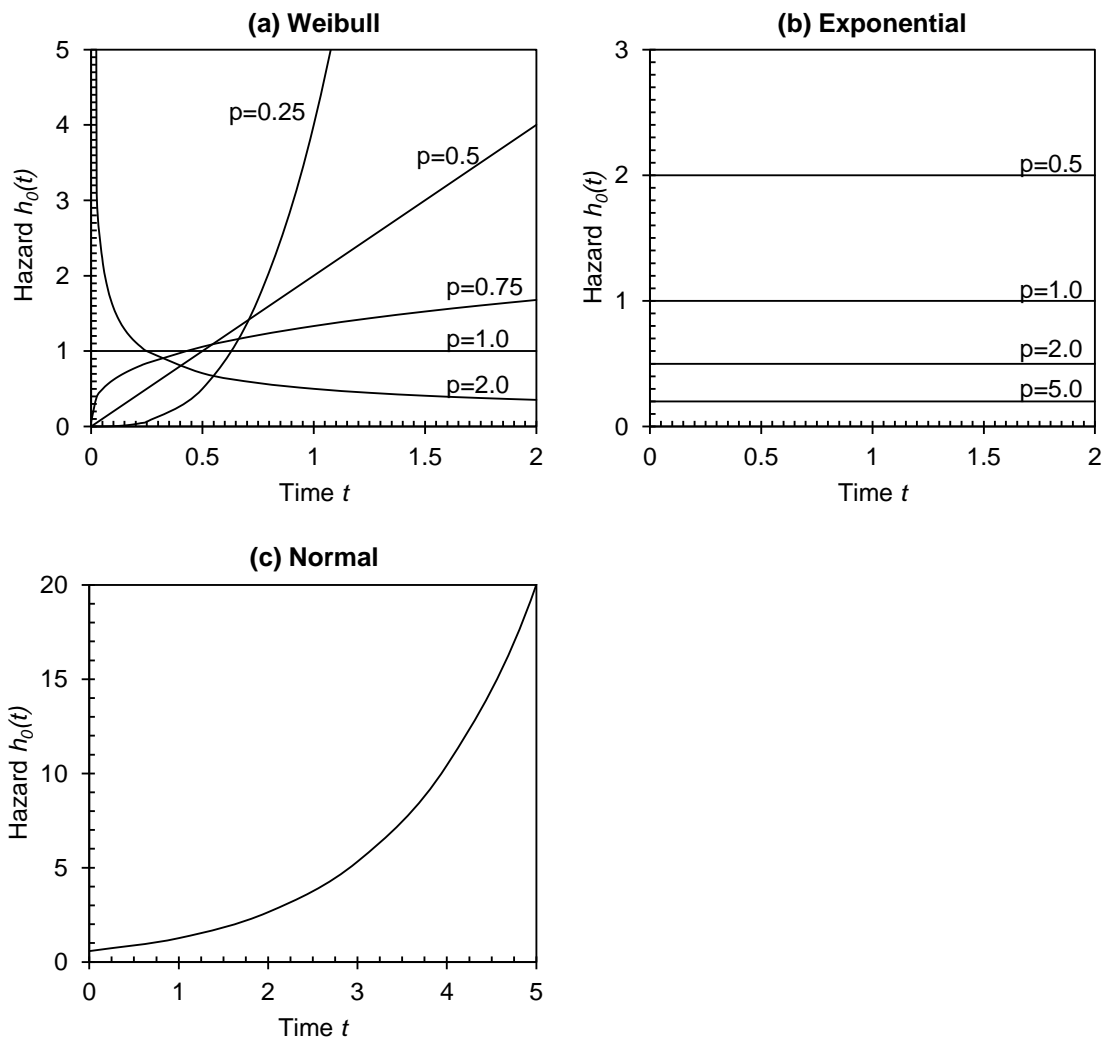


Figure 23: Alternative Baseline Hazard Functions
 Source: Own Illustration

Table 16: Specification of Alternative Baseline Hazard Functions

Model	$h_0(t)$
Weibull	$(1/p)t^{p-1}$
Exponential	$1/p$
Normal	$\phi(t)/\Phi(-t)$

Note. p = scale parameter; $\phi(\cdot)$ = probability density function; $\Phi(\cdot)$ = cumulative distribution function of the standard normal distribution

In order to account for the popularity of the logistic regression, I validate the robustness of the results with this alternative model. The regression equation of the logistic regression is (Blattberg et al., 2008, p. 380)

$$P(churn|f_{rb}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 f_{rb})}}, \quad (5.3)$$

where

f_{rb}, β_0, β_1 same meaning than in equation (5.2), and

$P(churn|f_{rb})$ = Probability that a customer with flat-rate bias f_{rb} churns.

5.3.1.4 Consequences of Flat-Rate Bias on Customer Lifetime Value

A customer's monetary loss due flat-rate bias is the company's monetary gain. And as it is basically pure profit it has a strong impact on customer profitability and hence CLV. The concrete monetary effect can be quantified based on the results of the survival analysis. The survival analysis yields an estimate for the percent-change c in average lifetime duration d per Euro increase of monetary loss due to flat-rate bias f_{rb} . This allows to formulate the average lifetime of customers with flat-rate bias f_{rb} as $d_{f_{rb}} = d(1 + c)^{f_{rb}}$. Because retention rate r and average lifetime duration can be related by $d = \frac{1}{(1-r)}$ as an approximation (compare section 2.3.2), the retention rate can be formulated with respect to monetary loss due to flat-rate bias f_{rb} as

$$r_{f_{rb}} = 1 - \frac{1 - r}{(1 + c)^{f_{rb}}}, \quad (5.4)$$

where

f_{rb}, r, c have the same meaning as above, and

$r_{f_{rb}}$ = average retention rate of customers with flat-rate bias f_{rb} .

And finally with the formulation of CLV with respect to gross margin and retention rate in equation 2.4, I can assess the impact the flat-rate bias on CLV and its percentage change respectively as a function of flat-rate bias as

$$CLV(frb) = (m + frb) \frac{r_{frb}}{1 + i - r_{frb}}, \quad (5.5)$$

$$\Delta_{CLV}(frb) = \frac{CLV(frb) - CLV(0)}{CLV(0)}, \quad (5.6)$$

where

frb, r_{frb} have the same meaning as in (5.4), and

m = gross margin, and

i = risk-adjusted interest rate.

5.3.2 Empirical Findings

5.3.2.1 Consequences of Flat-Rate Bias on Tariff-Switching and Churn

In Table 17 I provide churn and switching probabilities of users with and without flat-rate bias according to the two criteria. My results show that flat-rate bias does not have a significant impact on the switching probability. Hence I reject H_{1a} . In contrast, users who exhibit flat-rate bias overall have a 2.74 percentage points (7.99%) higher churn probability than users without. This difference is even more pronounced for the stricter second criterion: users that always have a flat-rate bias have 11.22 percentage points (34.34%) higher risk of cancellation. Both differences are significant at $p < .01$ level and thus support H_{2a} .

Table 17: Differences in Churn and Tariff Switching Probabilities

	Criterion "Overall"			Criterion "Always"		
	No FRB	FRB	Delta	No FRB	FRB	Delta
Switch	17.36 %	16.38 %	-.98pp [†]	16.62 %	17.86 %	1.24pp [†]
Churn	34.28 %	37.02 %	2.74pp ^{**}	32.67 %	43.89 %	11.22pp ^{**}

Note. ** = $p < 0.01$; † = not significant

I further examine whether this increase in the churn and tariff-switching probabilities specifically depend on the amount of monetary loss due to flat-rate bias. For this analysis I use survival analysis with several specifications of the

hazard function in an exploratory analysis. The comparison of the respective model fits according to the AIC test statistic is shown in Table 18 (see Appendix A.2 for a short explanation). As can be seen, this test confirms that the Weibull model is most the appropriate specification. Therefore I select the Weibull hazard model for further analysis.

Table 18: Relative Goodness of Fit of Hazard Model Specifications

Model	Switch		Churn	
	LL	AIC	LL	AIC
Cox	-14,293	28,588	-37,132	74,266
Weibull	-4,929	9,863	-11,218	22,444
Exponential	-5,090	10,183	-11,233	22,470
Normal	-9,014	18,028	-20,809	41,624

Note. LL = Log Likelihood; AIC = Akaike's Information Criterion

The results of the Weibull survival analysis (Table 19) support the previous analysis. In line with the results for H_{1a} , I did not find a significant impact of the amount of flat-rate bias on the tariff switching probabilities. Hence I also reject H_{1b} . However for the churn probability, the results are significant and show that each one Euro increase in the monetary loss prompts a decrease of customership duration by $-.89\%$. Thus H_{2b} is supported. I depict, in Figure 24, the results in the form of Kaplan-Meier curves of the survival distribution functions, plotted with stratification by the amount of monetary loss due to the flat-rate bias.

Table 19: Results of Weibull Survival Model

Variable	β_1	σ	95% CI	AF	χ^2	p
Model 1 (Churn)						
FRB amount	-.0089	.0021	-.0130 to -.0048	.9911	18.31	<.01
Scale	.9221	.0140	.8951 to .9499			
Model 1 (Switch)						
FRB amount	.0014	.0023	-.0031 to .0059	1.0014	.38	.54
Scale	.6138	.0154	.5843 to .6448			

Note. CI = Confidence Interval; AF = Acceleration Factor (e^{β_1})

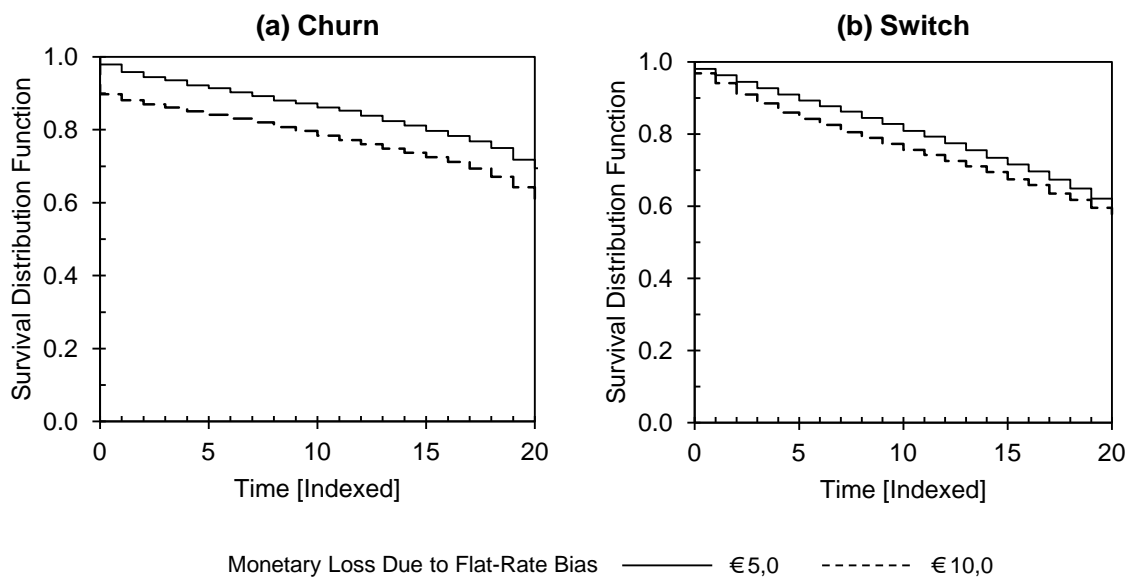


Figure 24: Kaplan-Meier Curves with Stratification on Monthly Average Monetary Loss Due to Flat-Rate Bias
Source: Own Illustration

For both models the scale parameter is smaller than 1, indicating a general increasing trend in the baseline churn probability over time. This is in line with my finding in chapter 1.

As for any other regression, in order for inferences to be valid, the fitted models must provide an adequate summary of the data. It is recommended to validate the underlying assumptions and goodness-of-fit with three analyses (Allison, 2010, p. 98; Hosmer et al., 2008, pp. 179, 257; Kleinbaum and M. Klein, 2005). First one can take use of a unique property to the Weibull model that if the AFT assumption (and hence the PH assumption) holds, the plot of $\log[-\log(S(t))]$ is linear with $\log(\text{time})$; and in particular stratification on covariates will produce parallel straight lines (D. R. Cox and Oakes, 1984, p. 79; Kleinbaum and M. Klein, 2005, p. 274). As Figure 25 shows, all lines are almost perfectly straight and remarkably parallel, hence supporting the model validity.

Likewise using a graphical inspection, the overall-goodness-of-fit can be validated by comparing the nonparametric Kaplan-Maier cumulative hazard to the model-based estimates of the cumulative hazards. If the parametric model is correct, this plot should follow a straight line through the origin with a slope of 1 (D. R. Cox and Snell, 1968; Hosmer et al., 2008, p. 257). As can be seen in Figure 26, the plot

for the churn model satisfies this requirement, deviates however considerably for the tariff switching model.

And finally the assessment of fit is completed by using the Grønnesby-Borgan test (Grønnesby and Borgan, 1996; May and Hosmer, 1998), which—in simple terms—compares the number of events that are observed with those that are expected on the basis of the estimation from the model. In this very popular test, subjects are grouped by their ranked estimated risk score in G groups. The model fit is acceptable if a score test of the model with accordingly added $G - 1$ design variables does not indicate a significant improvement over the original model. This test likewise confirms the validity of the Weibull survival model at least for the churn model ($Q = .1497$). The tariff switching model which includes the Grønnesby-Borgan design variables however fits significantly better ($Q < .01$) than the original model, hence indicating unsuitability of the assumptions.

All three tests taken together strongly support the validity of the Weibull churn survival model, however are inconsistent for the Weibull tariff switching survival model. Though Hosmer, Lemeshow, and May (2008, p. 269) note that inconsistent results "are typical of those often encountered in practice where some analyses support model fit while others do not" and recommend a qualitative decision, I do not want to place too much emphasis on this model. Besides, the very basic group comparison does not show significant impact of flat-rate bias on tariff switching behavior in the first place.

Finally, I further validate the robustness of these results by additionally conducting a logistic regression (Table 20) and Cox proportional hazard model (Table 21). For the logistic regression, I again find a statistically significant effect of the amount of monetary loss due to the flat-rate bias only on the churn probability, with an odds ratio of 1.015. Also the Cox proportional hazard model for the churn model shows a significant increase in the hazard ratio of likewise 1.5%; and the results for the switch model again lack significance. Hence both alternative models support the findings of the primary model indicating that each Euro increase of the amount of monetary loss due to flat-rate bias increases churn probability by 1.5%.

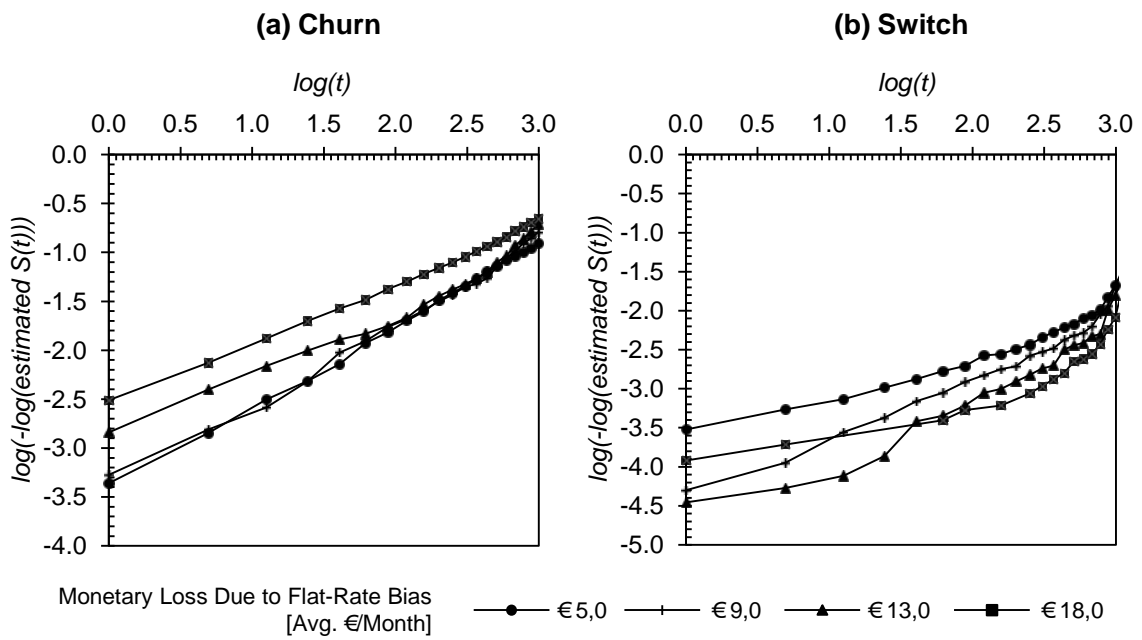


Figure 25: Stratification of $-\text{Log}(S(t))$ with $\text{Log}(\text{time})$ on Amount of Monetary Loss Due to Flat-Rate Bias
 Source: Own Illustration

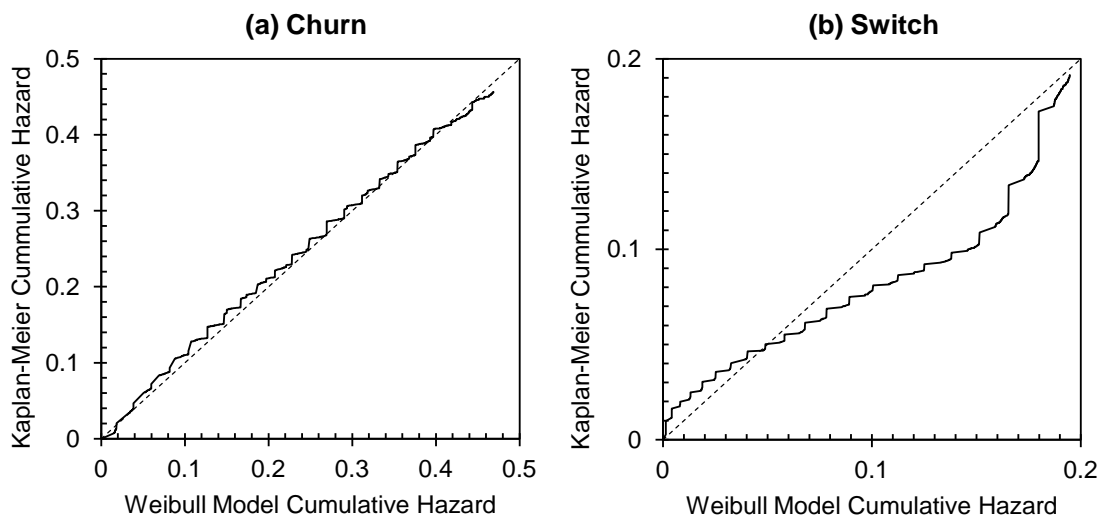


Figure 26: Kaplan-Meier Cumulative Hazards vs. Model Estimates
 Source: Own Illustration

Table 20: Results of Logistic Regression Model

Variable	α	δ	OR	OR 95% CI	χ^2	p
<i>Model 1 (Churn)</i>						
FRB amount	.0149	0.0027	1.015	1.010 to 1.020	29.41	<.0001
<i>Model 2 (Switch)</i>						
FRB amount	-.0020	0.0040	.998	.990 to 1.006	0.25	.6189

Note. δ = standard deviation; CI = confidence interval; OR = odds ratio (e^α).

Table 21: Results of Cox Proportional Hazard Survival Model

Variable	α	δ	HR	HR 95% CI	χ^2	p
<i>Model 1 (Churn)</i>						
FRB amount	.0150	0.0022	1.015	1.011 to 1.019	47.39	<.0001
<i>Model 2 (Switch)</i>						
FRB amount	-.0026	.0036	1.003	.995 to 1.010	.50	.4789

Note. δ = standard deviation; CI = confidence interval; HR = hazard ratio (e^α).

5.3.2.2 Consequences of Flat-Rate Bias on Customer Lifetime Value

From the results of the Weibull survival model derives that, in the present dataset, each one Euro increase of the flat-rate bias lowers the average customer lifetime by -0.89%, such that it also has a negative effect on the CLV. However on the other hand, flat-rate bias increases the profit margin; therefore it has also a positive impact on CLV. In combination, I find the impact of flat-rate bias on CLV to be overall in an inversely U-shaped relationship with the amount of monetary loss due to flat-rate bias³³ (see Figure 27). Though this relationship theoretically has a vertex at around 55 Euro, the CLV monotonically increases within the reasonable interval, in that the maximum amount of flat-rate bias is limited by the price of the flat-rate of around 25 Euro gross. Thus, despite increasing churn rates, the flat-rate bias overall exerts a positive effect on the CLV among my sample.

³³ Assuming 40% gross profit margin and an annual discount rate of 7%.

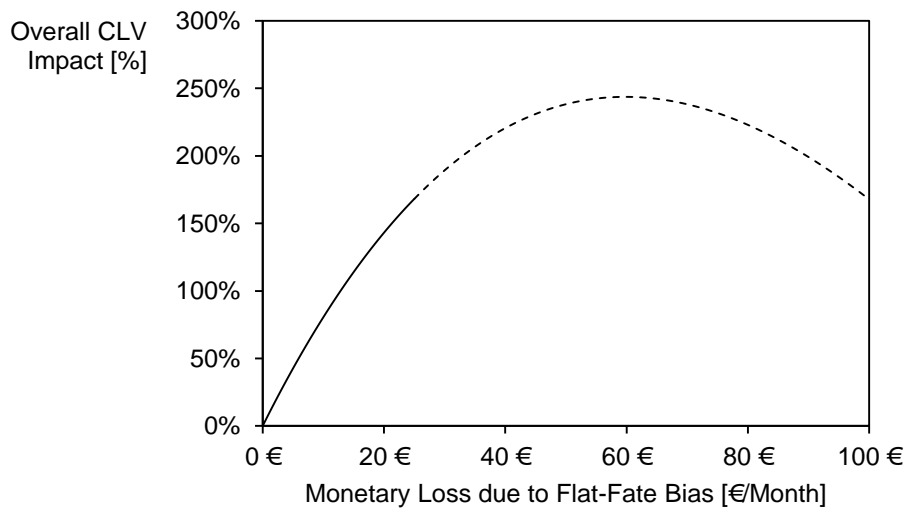


Figure 27: CLV Impact of Monetary Loss Due to Flat-Rate Bias
Source: Own Illustration

5.3.3 Summary of Transactional Study

While I did not observe a significant effect of flat-rate bias on switching probabilities, my transactional study showed that flat-rate bias leads to a significantly higher churn probability. With my survival analysis I could show that this increase specifically depends on the amount of monetary loss due to flat-rate bias. Overall, I found the CLV impact to be in an inversely U-shaped relationship with flat-rate bias.

The results of this survival analysis also confirm the finding of a general increasing trend in churn probability over time (compare section 3.4.2). I found the Weibull scale parameter in the survival analysis to be larger than 0.5 and smaller than 1, which indicates a general increasing hazard at a decreasing rate (compare section 5.3.1.3). In the context of this study, this increase of churn probability can also be led back to the sustainability of the flat-rate bias effects: As a user gains experience with the flat-rate, the effect of overestimation diminishes, and, in line with economic theory, his propensity to leave increases. Similarly with increasing service usage, customers learn about their actual usage pattern and hence their perceived risk of high charges decreases (compare sections 2.4.4 and 2.4.5). Consequently, the insurance effect should, too, wear off.

These results are in line with existing research confirming the existence of flat-rate bias (Della Vigna and Malmendier, 2006; Kridel et al., 1993; Mitchell and Vogelsang, 1991; Nunes, 2000). Also in terms of prevalence of flat-rate bias, my results are consistent with those from other studies (e.g., 42% in this study as compared to 38%, 45%, and 76% in other studies, see section 4.4.1).

However, my results and previous findings do deviate regarding the concrete consequences of flat-rate bias. Whereas both Lambrecht and Skiera (2006) and I find that some customers react if they pay too much with their flat-rate, the type of consequences is exactly oppositional (see Table 22). Customers with a flat-rate bias in the sample of Lambrecht and Skiera (2006) show a significantly increased switching behavior, whereas customers in my sample have a significantly higher churn rate. Hence in both studies the degree of reactivity is similar however the actual 'direction' of the customer reaction differs with regard to loyalty.

Table 22: Comparison of My Results with Existing Research

Significant Increase of...	Lambrecht and Skiera (2006)	My Results
switching (overall)	<i>n/s</i>	<i>n/s</i>
switching (allways)	~13pp higher switching rate ^a	<i>n/s</i>
churn (overall)	<i>n/s</i>	1.8pp higher churn rate
churn (allways)	<i>n/s</i>	7.6pp higher churn rate

Note. *n/s* = no significant difference; *a* = estimate based on reported percentage point changes for 5 month; figures annualized.

One reason could lie in methodological shortcomings of the study of Lambrecht and Skiera (2006) as pointed out in section 4.4.4. However, this would mainly explain the difference regarding churn, but not regarding switching. Assuming that the sample from Lambrecht and Skiera (2006) is from a low-cost context³⁴, another explanation for these differences could lie in the hypothesized effect of the competitive position on the concrete consequences (see section 5.2.3).

First, I find a lower general reactivity (i.e., switch plus churn) in my dataset which is from a premium provider. This would be in line with H_3 , according to which a

³⁴ I contacted the authors however they could not validate this assumption due to confidentiality agreements.

higher price sensitivity of low-cost provider customers leads to a higher reactivity. And second, the type of reaction is exactly oppositional. Whereas Lambrecht and Skiera (2006) find flat-rate bias to only act significantly on tariff switching probabilities, in the present sample, customers exhibiting flat-rate bias show significant differences only with regard to churn rates. This in turn is in line with H₄, which—drawing from social exchange theory—predicts higher churn probabilities for premium customers due to more attractive alternatives. The premium service provider in my sample has a relatively high price point in the market, hence it is very likely that cheaper competitive offers drove churn in this case. In contrast, the attractiveness of competitive offers for low-cost provider customers instead should be very low due to the already low price level leaving switching as the only way to economically improve the tariff choice for customers.

Though obviously this observation only represents anecdotal evidence rather than a proof in a statistical sense, it adds qualitative support for the moderating role of the competitive position of the provider. Following up on this, in the next section I therefore conduct a further experimental study analyzing the impact of the competitive position of the service provider on customer tariff switching and churn behavior.

5.4 Experimental Study

5.4.1 Research Design

To investigate the impact of a service provider's competitive position on the consequences of a flat-rate bias, I conducted an experimental study in the mobile telecommunications context. First, I compiled a tariff database with details about relevant mobile telecommunication flat-rates available in the German market, to assess price levels and savings potentials (Table 23). Beyond common market knowledge, I identified relevant service providers and tariffs from a tariff comparison website³⁵, hence, following typical information search behavior of consumers (Bakos, 1998). The tariff used for comparison was an all-net flat-rate including voice minutes to all German fixed and mobile telecommunications

³⁵ <http://www.handyflatrate-preisvergleich.de/>; reference time was summer 2010.

networks as this is the most distinct flat-rate tariff. More specifically, I used the regular monthly rates for two year contracts. Effects of temporary promotional offers were excluded. I segmented the operators in low-cost and premium providers based on three expert interviews (Figure 28). The experts were asked to rate the operators with respect to several criteria. These included brand image, advertising expenditure, retail network, technical infrastructure, service quality, and price level (Choi et al., 2001).

Next, I conducted a survey among 211 telecommunications flat-rate customers using a convenience sample, which I recruited online (see Appendix A.3). Basic demographic information of this sample is summarized in Table 24.

Table 23: Tariff Database of German All-Net Flat-Rates

Mobile Operator	Tariff Name	Market Segment	Monthly Fee [€]	Average Monthly Fee [€]
Phonex	All-In-Flat	Low-cost	37.90	
1&1	All-Net-Flat	Low-cost	39.99	Low-cost segment: 38.91
Drillisch Telecom	All-In-Flat	Low-cost	37.90	
Prima	All-Net-Flat	Low-cost	39.85	
Base	Allnet-Flat	Medium	50.00	Medium and Premium segment: 66.84
Flexmobil	Extra	Medium	64.95	
Simfix	Voll-Flat	Medium	59.95	
Congstar	Full-Flat	Medium	59.99	
Vodafone	Superflat-Allnet	Premium	79.95	Premium segment: 83.28
Blackandmine	Allflat	Premium	79.95	
Deutsche Telekom	Compl.-Mobile-XL	Premium	89.95	

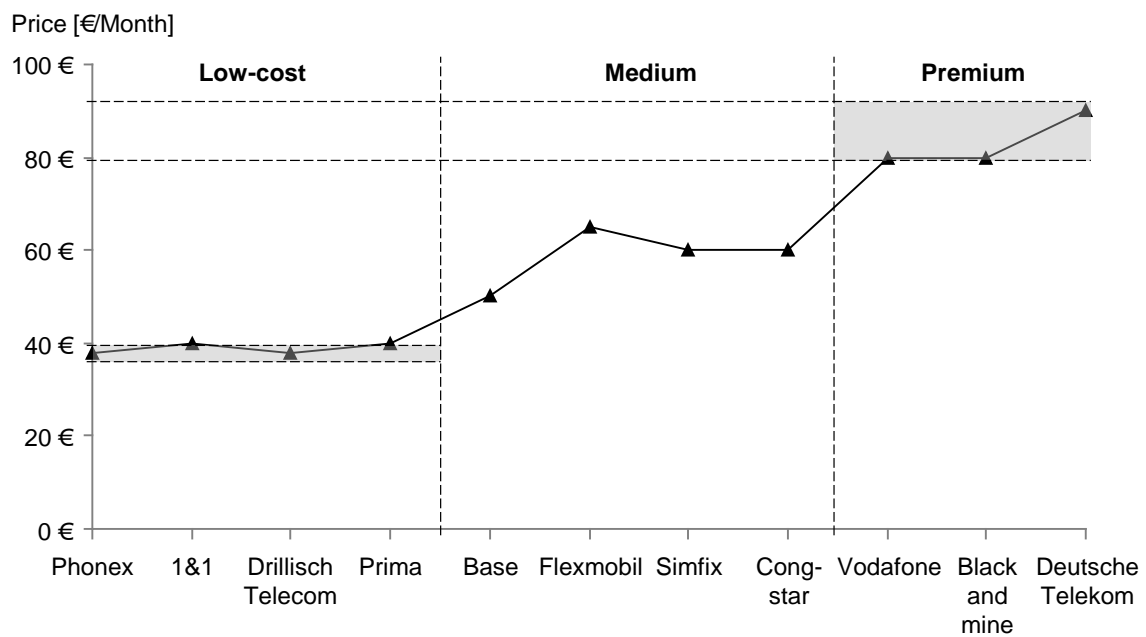


Figure 28: Price Distribution of German All-Net Flat-Rates
Source: Own Illustration

Table 24: Socio-Demographic Characteristics of Respondents

Criterion	Value	%
<i>Gender</i>	1: Male	62%
	2: Female	38%
<i>Age</i>	15-25 years	20%
	25-45 years	77%
	45-65 years	3%
<i>Gross Household Income</i>	1: < €1,500 per month	14%
	2: €1,500 - €2,499 per month	9%
	3: €2,500 - €3,499 per month	12%
	4: €3,500 - €4,499 per month	17%
	5: €4,500 - €5,499 per month	11%
	6: €5,500 - €6,499 per month	6%
	7: €6,500 - €7,499 per month	7%
	8: > € 7,500 per month	24%

I first provided them with introductory information, which defined pay-per-use, volume packages, and flat-rate pricing to ensure that all respondents have the same understanding of the relevant tariffs. Customers who had pay-per-use pricing were filtered out while, in line with the transactional study (see section 5.3.2.1) and other research (Heidenreich and Handrich, 2010; Lambrecht and Skiera, 2006), I treated customers with volume packages as flat-rate customers (with respectively adjusted wording throughout the survey).

In order to avoid potential endogeneity problems, I used two general experimental set-ups, assigning the respondents randomly in two groups. (1) Group one had to complete the questionnaire in reference to their actual service provider. I asked them to name this current service provider, to classify them subsequently as premium or low-cost service provider customers. Next they had to state their current voice tariff and monthly bill amount. With this approach, I gained data from real premium and low-cost customers, but I run the risk of endogeneity (Villas-Boas and Winer, 1999). Therefore (2) in the second group, respondents were randomly assigned to hypothetical scenarios: half of them were asked to imagine being customers of the hypothetical low-cost operator "CheapTel"; and the other half being customers of the premium provider "PrimeTel". I provided a short description of the qualities of each in terms of their image, service level, and pricing.

The monthly fee for the flat-rate of CheapTel was 40 Euro and 80 Euro for PrimeTel. These prices reflect typical prices of the low-cost and premium segment of the German market according to my tariff database. While this approach eliminates potential endogeneity problems, it relies on the respondents' ability to imagine being customers of a hypothetical provider.

Because in such an artificial experimental condition it is not possible to measure the awareness of having a flat-rate bias (i.e., the probability of its discovery), the respondents were confronted with the following statement: "Scientific research has shown that many flat-rate customers do not leverage their tariff and waste money compared to pay-per-use pricing." After thus priming them to believe they might exhibit a flat-rate bias, they were instructed next: "Assume you could quit your current flat-rate contract immediately without any switching cost and you

could keep your current telephone number. How much savings compared to your current flat-rate tariff would be needed to make you switch to pay-per-use or churn to a pay-per-use offer from a competitor?" I measured price sensitivity twice—once for switching and once for churn—using a scale adopted from Van Westendorp's Price Sensitivity Meter (PSM; Westendorp, 1976). Respondents were asked to name four price deltas

- (PD₁) which price difference is so low you don't even consider switching/churning;
- PD₂) at which price delta you start thinking about switching/churning;
- (PD₃) which price difference would make sticking to the flat-rate really hard for you; and
- (PD₄) at which price delta would you definitely switch/churn?

5.4.2 Empirical Findings

Table 25 and Table 26 summarize the results for the real customers (group 1) and the hypothetical scenario (group 2). Independent samples t-tests among the real customers show for premium provider customers a significantly higher monthly bill value than for low-cost provider customers, thus confirming the classification.

Regarding intentions to switch/churn, both for the real customers and the hypothetical scenario, price sensitivity towards the monetary loss due to a flat-rate bias is higher among the low-cost than the premium segment (i.e., all price deltas are lower for customers in the low cost context). Possibly due to the small sample size, the results are however only statistically significant for the critical price deltas PD₃ and PD₄ for price sensitivity regarding churning. On average premium customers have a 3.20 Euro/ 3.20 Euro (real customers/ hypothetical scenario) higher tolerance than low cost-customers to barely not churn (T(55) = 2.0, p < 0.05/ T(93) = 2.2, p < 0.05); and 5.20 Euro/ 4.30 Euro to definitely churn (T(94) = 2.7, p < 0.05/ T(93) = 2.0, p < 0.05). Thus, overall, the reactivity is higher in the low-cost customers, in support of H₃. Socio-demographic characteristics do not differ significantly, thus can be ruled out as potential alternative explanation.

Table 25: Independent Samples T-Test of Price Sensitivities for Real Customers

	Premium (n=34)		Low-Cost (n=62)		df	T
	M	δ	M	δ		
Churn PD ₁	8.2	1.1	6.6	0.5	49	1.3
Churn PD ₂	13.5	1.5	10.6	0.7	50	1.8
Churn PD ₃	13.3	1.4	10.1	0.8	55	2.0*
Churn PD ₄	20.8	2.0	15.6	1.0	94	2.7*
Switching PD ₁	6.2	.9	5.5	.5	94	.7
Switching PD ₂	11.1	1.3	9.1	.7	94	1.4
Switching PD ₃	10.6	1.1	9.0	.8	94	1.1
Switching PD ₄	17.0	1.8	13.6	1.0	94	1.8
Gender	1.4	.1	1.4	.1	94	.2
Age	28.7	1.1	30.3	.9	94	-1.1
Income	5.2	.4	4.5	.3	94	1.1
Bill-value	56.0	7.4	35.0	2.5	43	2.7**

Note. M = mean; δ = standard deviation; df = degrees of freedom; * = $p < .05$;
 ** = $p < .01$; Levene's test for equality of variances was taken into account.

Table 26: Independent Samples T-Test of Price Sensitivities for Hypothetical Scenarios

	Premium (n=46)		Low-Cost (n=49)		df	T
	M	δ	M	δ		
Churn PD ₁	7.0	0.8	6.3	0.6	93	0.7
Churn PD ₂	11.1	1.2	9.7	1.0	93	0.9
Churn PD ₃	12.0	1.3	8.8	0.8	93	2.2*
Churn PD ₄	18.1	1.8	13.8	1.3	93	2.0*
Switching PD ₁	5.5	.6	6.2	.7	93	-.8
Switching PD ₂	9.7	1.0	9.5	1.0	93	.2
Switching PD ₃	9.9	1.1	8.4	.8	93	1.1
Switching PD ₄	16.3	1.7	13.1	1.3	93	1.5
Gender	1.3	.1	1.5	.1	93	-1.9
Age	29.8	.9	30.5	1.0	93	-.5
Income	4.6	.4	4.6	.3	93	.1
Bill-value	36.0	6.0	45.0	16.5	93	-.5

Note. M = mean; δ = standard deviation; df = degrees of freedom; * = $p < .05$;
 ** = $p < .01$; Levene's test for equality of variances was taken into account.

The concrete type of reaction (i.e. switch vs. churn) then is a combination of these sensitivities and actual achievable savings in the market. To this end I prepare price sensitivity curves to show cumulative churn probabilities with respect to achievable monthly savings for premium and low-cost customers based on the answers of the participants. I use the average price sensitivities of PD₃ and level PD₄ as an approximation of the churn-critical price delta, since the actual value should lie between "would barely not churn" and "definitely churn" (see Figure 29 and Figure 30). The higher price sensitivity or reactivity respectively of low cost customers is reflected in the steeper slope of the corresponding curve: The expected churn probability for a given monthly saving is higher in the case of low-cost service provider customers compared to premium service provider customers.

To contrast price sensitivity and the attractiveness of alternatives, I map the potential savings per segment against the respective price sensitivity curve. The potential savings for the low-cost segment depend on the difference of the average monthly fee (38.91 Euro) and the cheapest low-cost provider tariff (37.90 Euro), which is approximately one Euro. In the premium segment I use the difference between the average monthly premium provider fee (83.28 Euro) and the average monthly fee of the premium and medium segment operators (66.84 Euro), as premium provider customers seem unlikely to switch directly to no frills low-cost carriers. The expected savings in the premium segment this is at least 16 Euro, indicating the higher attractiveness of competitive offers for the premium segment. The intersections in Figure 29 and Figure 30 then indicate the expected churn rates in each segment for the real customers or the hypothetical scenario respectively.

Despite their higher price sensitivity, the achievable savings in the low-cost segment of one Euro leads to an expected cumulative churn of 0%; no respondent in the survey indicated a willingness to churn for a price delta of just one Euro. In contrast, the cumulative churn of premium customers, given achievable savings of ~16 Euro, would be ~47%. That is, despite the higher price sensitivity of low-cost customers, the financially most viable option in the absence of attractive competitive offers is to optimize their tariffs within the provider, i.e., by switching to pay-per-use options. In contrast, customers in the premium segment will find significant savings potential and, thus, are likely to not only switch their tariff but

also to change their provider. The competitive position of a service provider thus determines the consequences of flat-rate bias among its customers. Premium provider customers exhibit a higher churn risk, confirming hypothesis H₄.

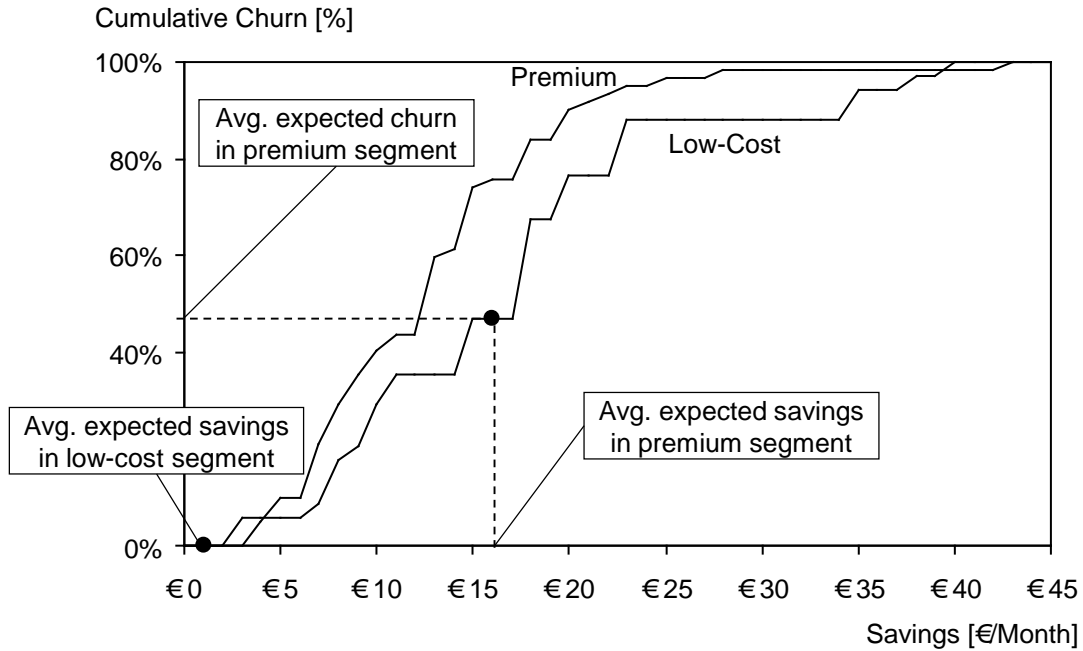


Figure 29: Price Sensitivity Curves and Savings Potential for Real Customers
Source: Own Illustration

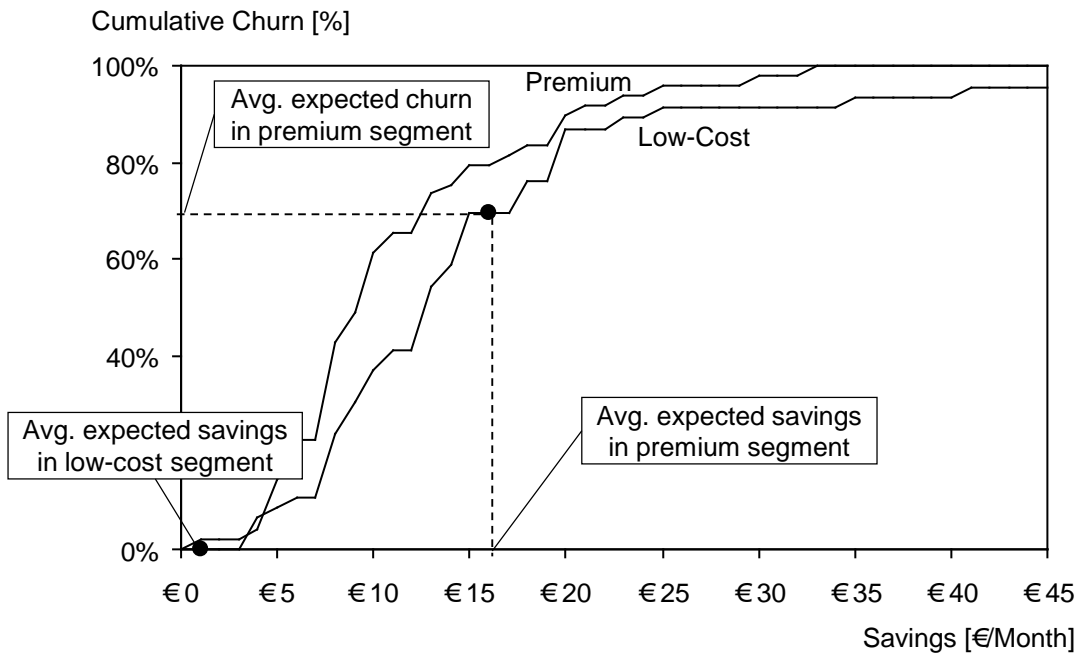


Figure 30: Price Sensitivity Curves and Savings Potential for Hypothetical Scenario
Source: Own Illustration

5.4.3 Summary of Experimental Study

Customers for whom the monetary loss due to their flat-rate bias exceeds the perceived value from the flat-rate bias effects have three options. (1) They can be inert and do not react to their loss; (2) they can switch to a pay-per-use tariff; or (3) churn to a competitor and capture price savings in a fast moving market. At this, the results of the experimental study show that the competitive position of the provider and the price sensitivity and achievable savings with alternative providers respectively, influence the consequences of flat-rate bias. On the one hand, based on my survey I found the general reactivity to monetary loss due to flat-rate bias of customers in a low-cost context to be higher than for customers of premium providers. On the other hand, the market study showed that while in the premium context high price differences exist (especially when also considering mid-tier providers), due to already a high price competition in low-cost contexts customers, here, can only achieve little savings by churning. If at all, the achievable savings only exceed the reported price deltas for which customers would switch tariffs.

5.5 Discussion

5.5.1 Synthesis of Findings from Transactional and Experimental Study

In this chapter, I investigated the consequences of flat-rate bias on customers' tariff switching and churn behavior and, consequently, on CLV; and furthermore the moderating role of competitive position of the service provider hereon. My results show that flat-rate bias significantly increases churn probability. Moreover, this increase in churn probability specifically is a function of the amount of monetary loss due to flat-rate bias. While in line with much of existing research on tariff choice, these findings contradict the results of Lambrecht and Skiera (2006a)—at least with regard to the concrete reaction, i.e., switch versus churn. Against this background, I found that the competitive position of the service provider acts as a moderator: while in premium contexts, customers tend to be less price sensitive than in a low cost context, prices of premium providers are much more diverging, which leads to greater savings potential. In the context of

this study, I found the savings potential to outweigh price sensitivity. Customers of premium service providers react with churn, while for customers of low cost providers, switching represents the economically most viable alternative.

Table 27: Summary of Findings

Research Question and Hypothesis	Study	
	Transactional	Experimental
RQ3 Consequences of Flat-Rate Bias on Customer Loyalty		
H _{1a} : Customers with a flat-rate bias have higher tariff-switching rates than customers without a flat-rate bias.	✘	n/a
H _{1b} : The higher the monetary losses that customers experience from flat-rate bias, the more likely they are to switch tariffs.	✘	n/a
H _{2a} : Customers with flat-rate bias have higher churn rates than customers without flat-rate bias.	✓	n/a
H _{2b} : The higher the monetary loss that customers experience due to flat-rate bias, the more likely they are to churn away from their service provider.	✓	n/a
RQ4 Moderating Role of the Service Provider's Market Position for the Consequences of Flat-Rate Bias		
H ₃ : Low-cost service provider customers exhibit greater reactivity (switching or churning) to flat-rate bias than do premium service provider customers.	n/a	✓
H ₄ : Premium service provider customers exhibit higher risk of churn than do low-cost service provider customers in response to flat-rate bias.	n/a	✓

Note. ✓ = hypothesis confirmed; ✘ = hypothesis not confirmed;
n/a = not applicable

5.5.2 Theoretical Contributions

The findings of my research contribute to flat-rate bias theory at least fourfold. First, I confirm, using transactional data of 21,490 customers (13,785 of which have a flat-rate tariff), the existence of flat-rate bias in relation to internet access. This adds to the body on this subject matter. Although flat-rate bias has been observed already in multiple cases (see section 4.4.1), my findings reaffirm the pervasiveness and relevance of this phenomenon.

Second, I find that customers who exhibit flat-rate bias have significantly higher churn probabilities. This finding contradicts to the current notion of flat-rate bias research predicting no negative impact on customer retention (Lambrecht and Skiera, 2006), but it is in line with general research on customer loyalty and tariff choice predicting customers to be more loyal if they are on the correct rate plan (Iyengar et al., 2007; Wong, 2010a). These findings also support predictions from attribution theory (C. Peterson et al., 1982), namely, that customers attribute a tariff choice failure to the provider and, as a consequence, lose loyalty and eventually churn. In addition, my findings reconfirm the relevance of standard economic theory (S. J. Brown and Sibley, 1986; Khan et al., 2004) for understanding customer loyalty in the context of flat-rate bias. Whereas behavioral decision research (Andersson and Engelberg, 2006) emphasizes the relevance of socio-psychological effects to explain why customers choose flat-rates even when pay-per-use would be more economical for them, my results show that in the long-term economic theory has high validity. Customers eventually regret their psychologically driven decisions and switch or churn to an economically more attractive tariff.

Third, my experimental study, comparing the reactivity of premium versus low-cost provider customers to flat-rate bias, provides a reasonable explanation for these controversial findings. As is shown in Table 22, customers in the sample of Lambrecht and Skiera (2006) express greater reactivity (switching or churn), with 13 percentage points compared to 7.6 percentage points in my dataset (see Table 22). A reason could be that the data from Lambrecht and Skiera (2006) is from a low-cost provider. My survey results show that low-cost provider customers show a higher price sensitivity (Hill, 1988; A. I. Murray, 1988) and that more price sensitive customers are more likely to engage in price search (Mehta et al., 2003).

The oppositional consequences could as well be explained by the providers' competitive positions (Porter 1980). Flat-rate bias in my data leads to churn, anticipated by the fact that the sample is from a premium service provider allowing for high savings from competitive offers. This confirms social exchange theory's notion that the attractiveness of competitive offers determines the strength of the customer-firm relationship or loyalty (Morgan and Hunt 1994). Finally, external attributions may foster churn even further. In contrast, the consequence of flat-rate bias in the case of Lambrecht and Skiera (2006) is switching.

In this case, it seems as if attribution theory is not as decisive in the low-cost segment as in the premium segment, perhaps because of the difference in the customer-firm relationships. Premium providers support their customers with individual and personal consultations to help them choose an appropriate tariff. Customers then might attribute a wrong tariff choice to a bad consultation. In the low-cost market, customers instead tend to rely on self-service over the internet, which makes external attributions harder. Then economic theory is the decisive element. The lack of alternatives from competitors forces low-cost provider customers to switch to the pay-per-use tariff offered by their current provider to avoid the transaction costs of churning to another provider (T. A. Burnham et al., 2003).

Fourth, by using transactional data I demonstrate that the increase in churn depends on the amount of monetary loss due to flat-rate bias, which is manifest in the influence of economic theory. Small amounts of monetary losses only lead to a slight increase in churn. A reason might be that the psychological value of the flat-rate bias effects—specifically the insurance and taxi-meter effects—lowers the negative impact. Customers find an additional value from not having to think about the cost while using a service or being safe from unexpectedly high bills. Increasing monetary losses will exceed these benefits though, and overestimation might become more salient, which offers no additional value. This finding indicates that effects from behavioral decision theory can compensate effects from standard economic theory up to a certain degree of economic loss. Lower monetary losses are bearable for customers, in line with behavioral economic

theory. But increasing monetary losses cause behavioral economics to give way to standard economic theory as a means to explain customer behavior.

5.5.3 Managerial Implications

Managers find themselves in a double bind. On the one hand, flat-rate bias is a significant source of profit since even a small bias of 2 – 3 Euros could increase customer profits by 20% – 50% (Heidenreich and Handrich, 2010; Lambrecht and Skiera, 2006). In the telecommunications industry, for example, up to half of the revenue is contributed by financially non-optimal rate plans (Wong, 2010a). On the other hand, management guides preach the focus on customer loyalty (Reichheld and Sasser, 1990; Reichheld and Teal, 1996; Reichheld, 2003). In this situation, my results can help managers decide how to handle customers with flat-rate bias, as well as to determine the right trade-off between revenue increases and lifetime maximization by taking their competitive position into account.

In the low-cost segment, there do not seem to arise any negative consequences of capitalizing on the customers' flat-rate bias for customer loyalty. Even if the value from flat-rate bias effects does not justify the monetary loss incurred from their non-optimal tariff choice, customers still tend to stay with the service provider due to a lack of attractive alternatives. Rather than to churn, my results suggest that they optimize their spending by choosing a more economical tariff offered by the same operator. For managers in this segment, a flat-rate bias thus is a desirable effect that they might try to foster, such as by triggering its causes through marketing activities (Lambrecht and Skiera, 2006).

In contrast, in the premium segment I observe flat-rate bias to have a negative impact on customer loyalty. In order to determine whether to proactively mitigate these tendencies, managers should assess the consequences both from a financial and a reputational perspective. First, since the consequences of flat-rate bias, i.e., increasing profits and decreasing customer lifetime, take a converse effect, managers need to assess the overall CLV impact. The overall CLV effect depends on the extent to which monetary loss due to flat-rate bias increases the customers' propensity to churn and the respective profit gains. In particular, the monetary loss due to flat-rate bias seems to be in an inversely U-shaped relationship with

CLV. Low amounts of monetary loss lead to only slight decreases in customer lifetime. From a provider's perspective, this situation indicates additional revenues that exceed foregone revenues due to the decrease in customer lifetime. Above a certain level though, the relationship changes. After the vertex of the inversely U-shaped curve, increased churn devours any additional revenues and leads to a negative impact of the flat-rate bias on the CLV. In the present context, I observe in sum a positive effect. However, as Figure 31a (sensitivity analysis for various effect strengths—i.e., differing impact of one Euro monetary loss due to flat-rate bias on the average customer lifetime) and Figure 31b (sensitivity analysis for various customer profitability values—i.e., how valuable is the customer per month in Euros profit contribution) show, this effect could easily be negative in other contexts, such that doing nothing can be dangerous for managers.

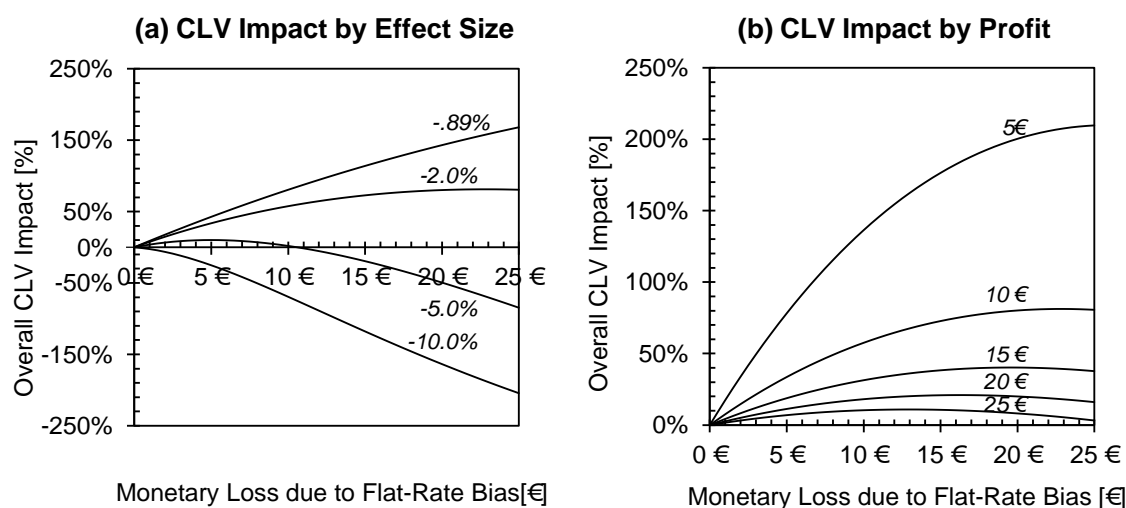


Figure 31: Relative CLV Change with Respect to Monetary Loss Due to Flat-Rate Bias and Effect Size or Profit³⁶

Source: Own Illustration

Second, managers should consider negative word-of-mouth as a result of flat-rate bias. Customers who experience a monetary loss due to their flat-rate bias are likely to attribute their poor tariff choice to the service provider causing negative sentiments and discontent with their relationship to the firm (Peterson et al., 1982; Riess et al., 1981). As a result of their dissatisfaction, they are likely to express their disappointment in the form of negative word-of-mouth (v. Wangenheim, 2005). This effect, too, is likely to be especially high at high levels of flat-rate bias.

³⁶ Average profit in Euro per month.

Hence, for both financial and reputational reasons, managers in premium contexts should consider managing customers with very high flat-rate bias levels proactively. For example, they could approach at-risk customers and offer to switch them to a pay-per-use tariff. Alternatively, to reduce flat-rate bias without affecting customer revenues, they might try to increase customers' usage levels. In the ISP context, for example, they could highlight or offer new content, such as online TV channels or complimentary video-on-demand vouchers.

5.5.4 Limitations and Further Research

I want to note that there are limitations of my work and point out the need for further research. First, my analyses all refer to the domain of telecommunications. Similar investigations in other industries could increase the external validity of my findings. However, the telecommunications industry represents the origins of flat-rate bias research, and results so far have matched those in other investigated sectors.

Second, in the survival analysis, I only included parameters directly related to flat-rate bias and thus cannot completely exclude an omitted variable bias. There may be more factors determining the reaction to flat-rate bias, such as household income or product involvement. Further research should replicate my study in other contexts and extend it by investigating the effects of other parameters to confirm my results. Similarly, when I investigated the service providers' competitive positioning as moderating factor for the consequences of flat-rate bias, I did not take into account if there are also other moderators influencing these consequences.

Third, the survey is comparably small in size. Due to privacy regulations, I was not able to match the survey with the transactional data. And finally, my measurement of the price sensitivity relies on self-reported price deltas which is subject to measurement errors and likely to be biased downwards (Gabor and Granger, 1974; Monroe, 1990, p. 107). However, since this study uses price sensitivity only as a comparative measure, this should not affect the validity of my results as long as there are no systematic deviations between low-cost and premium contexts.

I hope that the results of my study provide an impetus for future research in the domain of flat-rate bias. In addition to an increase of churn probability due to flat-rate bias, I also observed an increase in the baseline churn probability over time. I believe this is attributable to a wear-off of the overestimation effect as the user gains experience, but could not empirically substantiate this assumption. Research investigating the sustainability of the flat-rate bias effects would provide a valuable contribution. Finally, in an effort to provide further guidance for managers, future research should focus on strategies to mitigate increases in churn rates due to flat-rate bias. In many industries, especially in the mobile telecommunications industry, several companies are introducing pricing schemes that prevent or at least attenuate flat-rate bias, such as 'flex' rate plans that give subscribers the best service rate based on their actual usage (Wong, 2010a). These options could serve as a basis for scholars to derive best practices.

5.5.5 Outlook: Conceptual Model of Flat-Rate Bias Consequences

In the previous sections, I investigated several aspects of consequences of flat-rate bias. Implicitly, I already divided the process of consequences in two conceptual steps: First, reaction to flat-rate bias, which depends at least partly on the extent of flat-rate bias, and second, the concrete direction of the reaction (i.e., switch or churn), for which the competitive position of the service provider is an important moderator. In this section I argue that these are only two steps in an interrelated sequence of many others which can be conceptualized as a funnel (see Figure 32). However, as research is scarce on this topic, this discussion will remain conceptual and only base on clues from related research. Rather than concrete findings, it represents a structured set of propositions which might be addressed by future research.

Obviously, the basis (1) is all customers with a flat-rate tariff. Only a part of them exhibit a flat-rate bias. These customers can further be distinguished by whether they only objectively exhibit a flat-rate bias (2) or whether they actually perceive this bias as a loss (3). Two effects are likely to act as catalyst for the transition to the latter step. First: the subjective utility of flat-rate bias effects. As was stated in section 5.2, in contrast to the overestimation effect, the other three flat-rate bias effects (insurance effect, taximeter effect, and convenience effect) represent a

value to the customer. Consequently, in the consumer's subjective evaluation they will be imputed to the cost of the flat-rate. Therefore, even though a customer might mathematically exhibit a flat-rate bias, in terms of his perceived value he might not. And second: awareness. In order for a user to realize that he is paying too much, he needs to compare and evaluate the value of alternative (pay-per-use) tariffs and providers. This is a cognitive effort on behalf of the user, that according to cognitive dissonance theory's selective exposure (compare section 2.4.6) he is unlikely to expend. Both effects—his subjective evaluation of flat-rate bias effects compared to his monetary loss and the probability of a customer going through this effort—are likely to depend on his price sensitivity and his involvement with the service.

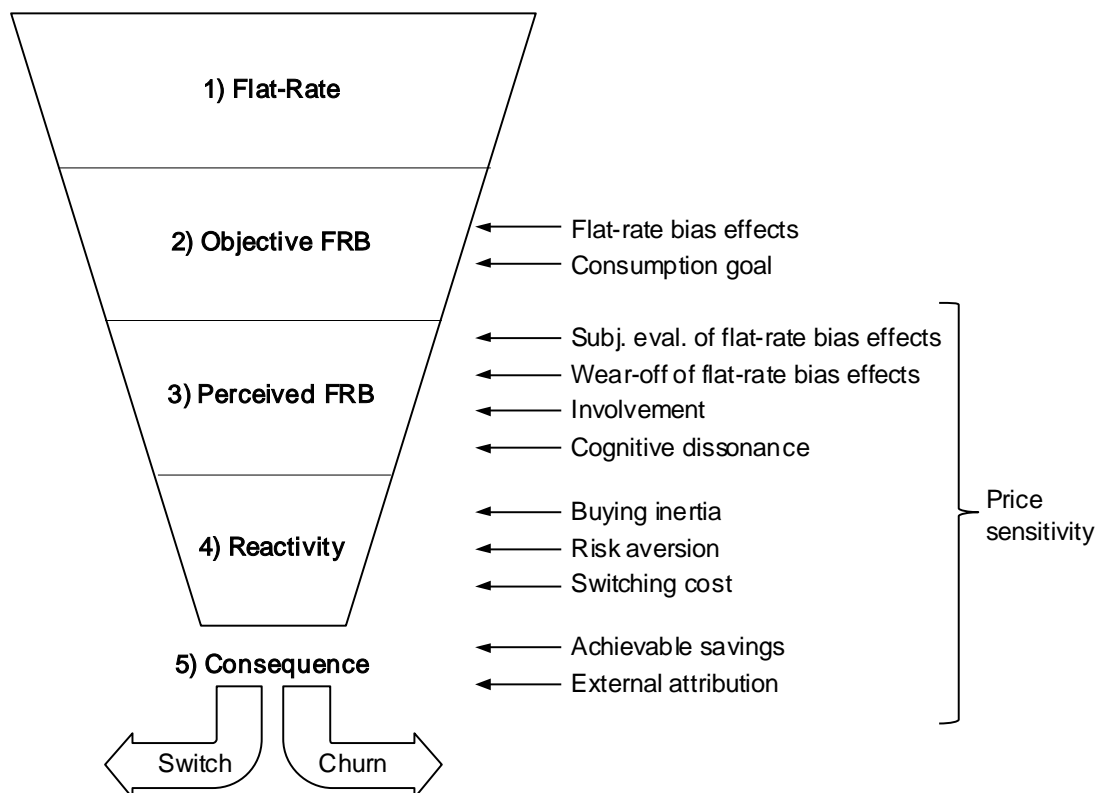


Figure 32: Conceptual Model of the Flat-Rate Bias Funnel
Source: Own Illustration

For those customers who are aware of paying too much (in terms of their perceived subjective value) due to the flat-rate bias, the critical question is whether or not they react (4). Here, similar considerations as in section 2.4, such as buying inertia, perceived risk of switching to a new provider, the social context

of the relationship with the existing provider, and switching cost (T. A. Burnham et al., 2003), apply. Finally (5), the type of reaction depends on the savings potential of competitive offers, since the attractiveness of alternatives determines the strength of the customer relationship (Morgan and Hunt, 1994) and external attributions of customers towards their provider. This, again, is moderated by the individual price sensitivity.

6 Conclusion

6.1 Summary of Results

The goal of my study was to investigate the trends in the behavioral sources of customer profitability and the role of flat-rate pricing. In particular, I raised three research questions aiming to review the existing tenet that customer profitability increases over time and discuss its implications for flat-rate tariffs. Table 28 summarizes my results with regard to these.

Table 28: Summary of Results with Regard to Raised Research Questions

Research Question	Finding
RQ1: Do the customers' behavioral sources of profitability change over the course of their customer relationship duration and, if so, does this trend have a positive or negative effect?	Except for cross-buying, customer activity generally attenuates and churn probability increases. This trend is, however, likely to be context-specific.
RQ2: Does flat-rate bias increase tariff switching and customer churn?	In premium contexts, customers with flat-rate bias have significantly higher churn probability than customers without. The specific increase depends on the amount of monetary loss due to flat-rate bias. In low-cost contexts, however, customers rather optimize their spending by tariff switching due to low attractiveness of alternatives that might not justify switching costs.
RQ3: Is the market position of the service provider a moderator of flat-rate bias consequences?	

In Chapter 2, I introduced the basic theoretical foundation of value based CRM. In particular, I highlighted that while the benefits of relationship orientation for firms are apparent and can be lead back to superior economics of customer retention and the competitive advantage that customer-firm relationships provide,

the customer motivations for relational market behavior are ambivalent. Based on a review of relevant economic and behavioral theories, I showed that on the one hand relational market behavior represents a purposeful reduction of choice and, hence, contradicts e.g., standard microeconomic theory and variety seeking. On the other hand, it can be explained with efficiency gains and increased cognitive consistency. This ambiguity in theories is also reflected in previous research findings. Though the tenet of increasing customer profitability continues to enjoy widespread acceptance, I showed in my meta-analysis of 12 studies that a considerable amount of findings still conflict.

In an effort to improve on this situation, in chapter 3, I conducted a rigorous cross-industry empirical analysis of the development of the behavioral sources of customer profitability over a multiyear period based on an analysis of four datasets from non-contractual and two from contractual contexts. My results are remarkably consistently showing customer revenues and the three main exchange parameters (customer retention, purchase frequency, and spending levels) to decrease over time. Only with regard to cross-buying were my findings consistent with the prevailing notion. Overall, my results show an attenuating trend in the behavioral sources of customer profitability over the course of the relationship duration.

These findings are also of high relevance for flat-rate pricing as I pointed out in chapter 4. On the one hand, they highlight the positive revenue stabilization effect of flat-rates. On the other hand, a general decreasing trend in customer activity translates for flat-rate customers in an increasing monetary loss due to flat-rate bias. Flat-rate bias, which contradicts standard economic theory, according to which customers try to maximize their welfare and choose the rate that leads to minimal cost, is often explained drawing from behavioral theories with psychological benefits and a cognitive error on behalf of the consumer. In my discussion of these explanatory approaches I identified the lack of insight with regard to sustainability and consequences on customer loyalty of flat-rate bias.

Against this background—and keeping in mind that customer loyalty is one of marketing managers' key concerns—I investigated the consequences of flat-rate bias on customer loyalty in a longitudinal study in chapter 5. In an analysis of two

years transactional data of ISP customers, I found churn probabilities to be significantly higher for customers that exhibit a flat-rate bias. Furthermore, based on a survival analysis, I showed that this increase in churn rates specifically depends on the amount of monetary loss due to flat-rate bias. In contrast, I found no impact of flat-rate bias on tariff switching.

Acknowledging that these consequences do not solely depend on customer specifics, I furthermore investigated, whether they are also moderated by characteristics of the service provider. Based on an experimental study, I found the competitive position of a service provider to influence the concrete direction of the effect: while customers of both low-cost and premium providers in general react to the incurred loss with reviewing their choice, the former tend to optimize their spending by switching to a more suitable tariff at the same provider whereas the latter are more inclined to churn to a different operator.

Consequently, especially in premium contexts, flat-rate bias acts on the two main drivers of customer value with opposing effect. On the one hand, since flat-rate bias basically is pure profit, it increases the height of cash flows. On the other hand, it has negative impact on loyalty, hence, decreases customer lifetime. In a theoretical model based on my results, I found the overall effect of flat-rate bias to be related in an inversely U-shaped relationship with customer value: CLV increases until a certain amount of monetary loss due to flat-rate bias and then monotonically decreases. In my sample, this vertex did not occur within the practically relevant interval, which might, however, be different for other domains.

6.2 Theoretical Implications

I already discussed the implications of this work for marketing research and theory in detail in sections 3.5.2 and 5.5.2. This section is dedicated to outline the main implications from an overall perspective.

The first study in this dissertation—the empirical review of the development in the behavioral sources of customer profitability over time—had more of a

descriptive rather than theoretical focus. Nevertheless, I believe that the findings are relevant for the marketing domain also on a theoretical level. Most importantly, my results show that the present tenet of increasing customer profitability over the course of the relationship duration is a gross oversimplification. At the very least, this trend is context specific.

Moreover, I believe my results also hold implications for general theory underlying relationship marketing. Based on my discussion of relevant theories, I showed that many theories and concepts provide arguments both for and against relational market behavior of consumers. While most researchers so far concentrated on concepts in favor of a relationship orientation of consumers, one key implication of my work should be that it highlights also the importance of the concepts in favor for transactions-based purchasing. The decreasing trend in the behavioral sources of customer profitability which I found indicates the important role of, e.g., basic microeconomic considerations; variety seeking (learning theory); information seeking as risk reliever (risk theory); and reciprocation of relational engagement—both with respect to consequences of disappointment as well as discomfort due to respective obligations—and the attractiveness of alternatives (social exchange theory).

Likewise, researchers citing these theories usually implicitly assume that the setting of the exchange exhibits conditions that these theories explain. At this, my findings can be interpreted as reemphasis that this is not the case in many business-to-consumer contexts. Assumptions about the existence and specificity of relational investment (transaction cost theory); information asymmetry (principal-agent-theory); perceived riskiness of transactions (risk theory); and the existence of a social relationship of some form (social exchange theory) might not hold in many consumer markets with increasingly commoditized products and standardized, anonymous purchasing processes (Dumlupinar, 2009; Katz and C. Shapiro, 1985).

A similar ambiguity between theories exists also with regard to consequences of flat-rate bias. In my discussion of relevant theories, I identified three shortcomings of existing theories. (1) There is a conflict between current research (Lambrecht and Skiera, 2006) on the one side, which—drawing from behavioral economics—

predicts no impact of flat-rate bias on churn and both standard economic and general theory on tariff choice on the other side, according to which customers try to maximize their welfare and choose the rate that leads to minimal costs. Furthermore, (2) behavioral theories explain flat-rate bias with four psychological and behavioral effects but do not make any statements to the degree that these compensate a monetary loss. And (3), researchers so far only investigated these effects from a static perspective, so little is known about their extent over time.

The results of this work improve on this situation by taking a more differentiated view. First, my results resolve the conflicts between behavioral and standard economic theory with regard to provider-specific characteristics and the extent of flat-rate bias exhibited by the user. For one, I found the competitive position of the provider to be a moderator of the concrete consequences of flat-rate bias on customer loyalty. And for another, the finding that the increase in churn probability depends on the amount of monetary loss suggests that behavioral economic theory is applicable only to a certain extent. Or more precisely and second: that the psychological benefits of insurance, taximeter, and convenience effects represent a value, which, following economic theory, justifies monetary loss due to flat-rate bias only to some degree. Finally third, the progression in the baseline churn probability over time found with the survival analysis furthermore motivates the assumption that these effects are not constant but subject to a wear-off over time.

6.3 Managerial Implications

The implications of my results for practitioners have already been pointed out in detail in sections 3.5.3 and 5.5.3. This section summarizes and synthesizes the key findings jointly.

Flat-rates are enjoying increasing popularity for a wide variety of services and product classes. Marketing managers considering the introduction or further development of these tariff structures are, however, confronted with an ongoing discussion whether flat-rates create value by stabilizing customer revenues or destroy value by forgoing a potential increasing trend in customer activity and

spending. In big parts, this discussion is spurred by the notion of increasing customer profitability over time which has been 'silently promoted' to a generalized directive in many marketing functions. Against this background, my finding of a general attenuating trend provides a valuable contribution. It shows that this reasoning is at least a gross oversimplification and needs to be corrected to take a less optimistic view. Consequently the evidence is that flat-rates indeed hold the potential to be a viable pricing strategy by countervailing eroding customer revenues.

However, my findings also provide a cautionary note. With attenuating user activity the revenue stabilization effect of flat-rates induces flat-rate bias. Depending on the competitive position and the financial attractiveness of tariffs with alternative providers this can come at the cost of customer loyalty. While in low-cost contexts there seem to be no negative consequences of flat-rate bias with regard to customer lifetime, providers in premium context should carefully inspect the switching and churn behavior of their flat-rate biased customers. Notwithstanding industry and context specificity, my results motivate the following general advice to marketing managers:

The concrete CLV impact depends on the amount of monetary loss due to flat-rate bias, where for high amounts the negative consequences on customer lifetime can in the long run exceed short term profit gains. Therefore, first, they are advised to consider proactively managing customers with a high level of flat-rate bias to avoid financial and reputational losses. One possibility could be to offer the opportunity to switch the tariff or to increase these customers' usage levels by, e.g., pushing complementary offerings. Furthermore, my analyses show that the amount of monetary loss due to flat-rate bias is not static but increases over time. Consequently, the second advice is to continuously probe the extent and development over time. Then flat-rates can be a win-win situation for both customers and providers.

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Appendix

A.1 Additional Tables

Table 29: Description of Datasets (Cohort 2)

	Airline	Hard- ware	Fashion Retailer	General Retailer	Telco	Isp
Time span	10 qtrs	11 qtrs	7 qtrs	6 qtrs	9 qtrs	8 qtrs
Number of customers	5,153	8,603	7,671	9,545	2,080	9,108
Ø trans./ cust. p.a.	9.0 (δ 8.1)	16.4 (δ 13.9)	5.5 (δ 5.6)	7.5 (δ 8.2)	n/a	n/a
Ø revenue/ trans or mth	€213 (δ 207)	€36.5 (δ 68.3)	€124 (δ 174)	€122 (δ 174)	€114 [†] (δ 375)	€16.9 [†] (δ 22.8)
% right censored	32%	75%	72%	58%	74%	88%

[†] Overall per month

Table 30: Complete Regression Results

Aspect and Data Set	Mean [†]	β_1 time [†]	β_{dummy}	R ²
<i>Churn Probability</i>				
Airline	.097	.005**	.296**	.98
	.111	.009**	.194**	.97
Hardware	.036	.001**	-.007**	.63
	.039	.000	.003	.04
Fashion Retailer	.012	.001**	.013**	.99
	.032	.004**	.036**	.99
Gen. Merch. Retailer	.015	.003**	.001**	.86
	.061	.013**	.054**	.96
Telco	.034	.002**	.004	.86
	.035	.002**	.006	.79
ISP	.062	.002**	n/a	.68
	.063	.003**	n/a	.81
<i>Interpurchase times</i>				
Airline	.413	.038**	n/a	.25
	.386	.041**	n/a	.29
Hardware	.230	.037**	n/a	.25
	.226	.046**	n/a	.25
Fashion Retailer	.774	.085**	n/a	.53
	1.030	.235**	n/a	.54
Gen. Merch. Retailer	.469	.113**	n/a	.54
	.814	.361**	n/a	.58
Telco	n/a	n/a	n/a	n/a
	n/a	n/a	n/a	n/a
ISP	n/a	n/a	n/a	n/a
	n/a	n/a	n/a	n/a
<i>Spending levels</i>				
Airline	.958	-.014**	n/a	.61
	.957	-.020**	n/a	.63
Hardware	.808	-.020**	n/a	.22
	.807	-.026**	n/a	.26
Fashion Retailer	.813	-.029**	n/a	.19
	.847	-.025**	n/a	.29
Gen. Merch. Retailer	.770	-.030**	n/a	.21
	.829	-.028**	n/a	.34
Telco	n/a	n/a	n/a	n/a
	n/a	n/a	n/a	n/a
ISP	n/a	n/a	n/a	n/a
	n/a	n/a	n/a	n/a

(continued)

Aspect and Dataset	Mean [*]	β_1 time [*]	β_{dummy}	R ²
Overall Revenue				
Airline	1.997	-.025 [*]	<i>n/a</i>	.62
	1.944	-.043 ^{**}	<i>n/a</i>	.61
Hardware	2.264	-.060 ^{**}	<i>n/a</i>	.17
	2.394	-.083 ^{**}	<i>n/a</i>	.11
Fashion Retailer	1.052	-.050 ^{**}	<i>n/a</i>	.43
	1.039	.011	<i>n/a</i>	.47
Gen. Merch. Retailer	1.595	-.090 ^{**}	<i>n/a</i>	.30
	1.042	-.074 [*]	<i>n/a</i>	.53
Telco	261.403	-.119	<i>n/a</i>	.74
	342.080	.098	<i>n/a</i>	.78
ISP	49.807	-.295 ^{**}	<i>n/a</i>	.37
	50.208	-.319 ^{**}	<i>n/a</i>	.39
Cross Buying				
Airline	1.152	.007 ^{**}	<i>n/a</i>	.42
	1.122	.007 [*]	<i>n/a</i>	.45
Hardware	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
Fashion Retailer	1.850	.061 ^{**}	<i>n/a</i>	.43
	1.626	.039 ^{**}	<i>n/a</i>	.41
Gen. Merch. Retailer	2.106	.014 ^{**}	<i>n/a</i>	.53
	1.759	-.010 [*]	<i>n/a</i>	.51
Telco	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
ISP	1.155	.228 ^{**}	<i>n/a</i>	.46
	1.388	.207 ^{**}	<i>n/a</i>	.62

Note. ^{*} = normalized per quarter; ^{*} = p < .05; ^{**} = p < .01; *n/a* = not available; Cohort 1 in first row, Cohort 2 in second row;

Table 31: Results from NBD Regression Analysis for Cross-Buying in Cohort 2

Dataset	Time	LL	DF	Pearson χ^2
Airline	.0056*	-10,370	2,169	.10
Hardware Store	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
Fashion Retailer	.0264**	-5,167	5,434	.47
General Retailer	-.0092	-3,032	3,198	.57
Telco	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>
ISP	.4038**	-6,961	7,013	.70

Note. LL = Log-Likelihood; DF = degrees of freedom; *n/a* = not available;

* = $p < .05$; ** = $p < .01$

A.2 Introduction to Survival Analysis

Survival analysis is a set of statistical methods designed to study time to event data. Going back to mortality tables centuries ago, originally, the event of interest was death hence the term, 'survival analysis'. However especially in the last 50 years it further emerged to failure research and is today an integral tool for churn analysis (Li, 1995; T. C. Smith and B. Smith, 2001). Analysis of this type of data requires special techniques due to its typical feature that the event of interest does not necessarily occur for all subjects under consideration before the end of the observation period (i.e., censoring; compare section 3.3.3.2). In this situation, survival analysis is able to use all available data to estimate the survival probability, including data derived from subjects with censored observations. Additionally it incorporates time as a continuous variable rather than a dichotomous 'has churned'/'has not churned' indicator.

The focal constructs of survival analysis are the survival survivor function $S(t)$ and the hazard function $h(t)$. If T denotes the random variable for an object's survival time, then the survivor function gives the probability that the survival time is greater than t ; and the hazard function gives the instantaneous potential of the event to occur, given that the object has survived up to time t . Or more formal

$$S(t) = P(T > t), \text{ and} \tag{A.2.1}$$

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | t \geq T)}{\Delta t} . \tag{A.2.2}$$

While the survival function $S(t)$ as a probability can only take on values between 0 and 1, the hazard function $h(t)$ describes the hazard as a rate. This rate is the limit of the number of events per unit time divided by the number of subjects at risk as this time interval decreases and, hence, can take on any nonnegative value. Obviously both functions relate to familiar concepts from statistics: A specific survival time of a subject is a realization of the continuous variable T with

cumulative distribution function $F(t)$ and probability density function $f(t)$. $F(t)$ is in fact the opposite of the survival function given by $F(t) = 1 - S(t)$; and whereas $f(t)$ summarizes the concentration of survival lengths at each instant of time, the hazard function $h(t)$ summarizes this concentration conditioned on the survival up to that instant. Consequently, these functions can also be set in a mathematical one-to-one relationships by $S(t) = \exp\left[-\int_0^t h(u)du\right]$, $h(t) = -\left[\frac{dS(t)/dt}{S(t)}\right]$ and $f(t) = h(t)S(t)$. The key point is, that specifying one of the probability density function, the survivor function or the hazard function allows the others to be ascertained by the preceding formulas (Kleinbaum and M. Klein, 2005).

The nonparametric Kaplan-Meier estimator as the most frequently used estimator of the survival function (Hosmer et al., 2008, p. 59) has already briefly been described in section 3.3.3.2. As stated, the Kaplan-Meier estimator has limitations, especially if it comes to including more than one and scalar predictor variables. For this task Cox (1972) proposed a today very popular regression method know as Cox proportional hazard (PH) model, given by

$$h(t, \vec{X}) = h_0(t)e^{\sum_{i=1}^p \beta_i X_i}, \quad (\text{A.2.3})$$

Where

t = time,

$\vec{X} = (X_1, X_2, \dots, X_p)$ the set of predictor variables, and

β_t = regression coefficients.

It specifies the hazard functions as a product of two functions. The first, $h_0(t)$, is called the baseline hazard function and characterizes how the hazard function changes as a function of survival time. And the second function, $e^{\sum_{i=1}^p \beta_i X_i}$, characterizes how the hazard function changes with respect to covariates. Similar to the odds ratio in a logistic regression, the effect of the covariates is then interpreted as a 'relative risk'-type hazard ratio (HR)

$$HR(\vec{X}, \vec{X}^*) = \frac{h(t, \vec{X}^*)}{h(t, \vec{X})} = \frac{h_0(t)e^{\sum_{i=1}^p \beta_i X_i^*}}{h_0(t)e^{\sum_{i=1}^p \beta_i X_i}} = e^{\sum_{i=1}^p \beta_i (X_i^* - X_i)}, \quad (\text{A.2.4})$$

Where

t, β_t same meaning as in equation (A.2.3)

$\vec{X}^* = (X_1^*, X_2^*, \dots, X_s^*)$ the set of predictor variables of the focal object, and

$\vec{X} = (X_1, X_2, \dots, X_s)$ the set of predictor variables of the comparative object.

While it is evident that a hazard ratio greater than 1 indicates a harmful effect, its concrete effect on survival time or probabilities is less apparent. Since the HR is defined relative to the hazard rate, its relation to mean survival times and probabilities is likewise less clear and harder to understand. A hazard ratio of 2 means that, all other covariates held constant, per unit change of the respective predictor the hazard doubles, i.e., that at any time the number of subjects with respective covariate configuration having an event doubles.

The term '*proportional hazards*' refers to the fact that in expression A.2.4 covariates are multiplicatively related to the hazard and hence have a constant effect. While the baseline hazard may vary over time, since it cancels out in the HR, the HR is required to be constant. Or stated differently, that the hazard for one subject is proportional to any other subject, where proportionality is constant and in particular independent of time. From the above formulation follows also that the baseline hazard does not need to be specified which is why the Cox PH model is referred to as a semi-parametric model.

In many instances however full-parametric survival models can be more efficient and provide more meaningful results (May and Hosmer, 1998). In particular, the estimation of the baseline hazard functions allows making inferences on the actual survival time or churn probabilities, respectively (David W. Hosmer et al., 2008, p. 244). In particular, my finding of chapter 3, i.e., that churn probability

increases over time, motivates the use of the Weibull³⁷ hazard function which closely resembles the observed churn development.

$$h(t, \vec{X}) = pt^{p-1} e^{\sum_{i=1}^s \beta_i X_i}, \quad (\text{A.2.5})$$

where

t, \vec{X}, β_t same meaning as in equation (A.2.4)

p = the scale parameter.

Though in fact the Weibull model just like the Cox PH model is a proportional hazard model, it is typically estimated in the form of an accelerated failure time (AFT) model (see David W. Hosmer et al., 2008 for corresponding PH form). These are indeed the same models except that they follow different assumptions which leads to a differing parameterization (Kleinbaum and M. Klein, 2005, p. 271). While the effect of covariates in a PH model is multiplicative with respect to the hazard, for AFT models it is multiplicative with respect to survival time. Accordingly, while a hazard ratio measures association of covariates on the rather abstract hazard rate, the acceleration factor actually measures the 'stretching out' or contracting of survival times. Hence in contrast to the hazard ratio a factor greater than 1 actually implies a beneficial effect on survival. The concrete percentage change of survival time per unit increase of a predictor variable with coefficient β_i can be calculated as

$$\text{change} = e^{\beta_i} - 1. \quad (\text{A.2.6})$$

Among the estimation of the concrete impact on survival time, full-parametric models also estimate of the baseline hazard $h_0(t)$. This allows the decomposition of the hazard function in covariate specific effects from the general hazard development over time.

³⁷ This hazard function is named after the Weibull distribution of its probability function. This is because substituting $e^{\sum_{i=1}^s \beta_i X_i}$ with λ from A.2.5 follows that the survival function is $S(t) = e^{-\lambda t^p}$ and hence that $f(t) = \lambda p t^{p-1} e^{-\lambda t^p}$, which is the specification of the Weibull distribution with scale parameter p and shape parameter $1/\lambda$ (Weibull, 1951).

In a Weibull model, this overall development of the hazard rate is reflected in the scale parameter p as (Allison, 2010, p. 80)

$$p = \begin{cases} 0 < p < 0.5 & \text{Increasing hazard at decreasing rate} \\ p = 0.5 & \text{Increasing hazard at constant rate} \\ 0.5 < p < 1 & \text{Increasing hazard at decreasing rate} \\ p = 1 & \text{Constant hazard} \\ p > 1 & \text{Decreasing hazard.} \end{cases}$$

As for any other regression, in order for inferences to be valid, the fitted models must provide an adequate summary of the data. Because this assessment is for survival models not as straightforward as for other regression analyses I want to briefly give an overview of the employed techniques³⁸. Common it is recommended to validate the underlying assumptions and goodness-of-fit with three analyses (Allison, 2010, p. 98; Hosmer et al., 2008, p. 179, p. 257; Kleinbaum and M. Klein, 2005, p. 273). First one can take use of a unique property to the Weibull model that if the AFT assumption (and hence the PH assumption) holds, the plot of $\log[-\log(S(t))]$ is linear with the $\log(\text{time})$; and in particular stratification on covariates will produce parallel straight lines (Cox and Oakes, 1984, p. 79; Kleinbaum and Klein, 2005, p. 274). Likewise using a graphical inspection, the overall-goodness-of-fit can be validated by comparing the nonparametric Kaplan-Maier cumulative hazard to the model-based estimates of the cumulative hazards. If the parametric model is correct, this plot should follow a straight line through the origin with a slope of 1 (Cox and Snell, 1968; David W. Hosmer et al., 2008, p. 257). And finally the assessment of fit is completed by using the Grønnesby-Borgan test (Grønnesby and Borgan, 1996; May and Hosmer, 1998), which—in simple terms—compares the number of events that are observed with those that are expected on the basis of the estimation from the model. In this very popular test, subjects are grouped by their ranked estimated risk score in G groups. The model fit is acceptable if a score test of the model with accordingly added $G-1$ design variables does not indicate a significant improvement over the original model.

³⁸ For a detailed discussion refer to Hosmer, Lemeshow and May (Hosmer et al., 2008) who point out in this context (p. 170) that "a regression analysis of survival time is set apart from other regression models, the fact that the outcome variable is time to an event and the observed values may be incomplete or censored."

To compare these models g_i , the Akaike information criterion (AIC; Akaike, 1974) and their relative likelihood Akaike weights w_i can be used as basis for model selection (Akaike, 1983; Burnham and D. R. Anderson, 2002, p. 75).

$$AIC_i = 2k - 2LL, \quad (\text{A.2.7})$$

$$w_i = \frac{\mathcal{L}(g_i|x)}{\sum_{r=1}^R \mathcal{L}(g_r|x)}, \quad (\text{A.2.8})$$

Where

k = number of parameters in the statistical model,

LL = log likelihood of the model,

$\mathcal{L}(g_i|x)$ = the LL of model g_i given the data x , approximated by $e^{-\frac{1}{2}\Delta_i}$, and

$\Delta_i = AIC_i - \min_r(AIC_r)$.

A.3 Survey among Mobile Telecommunications Customers

Einleitung

In der Befragung geht es primär um das Thema Sprachtelefonie. Versuchen Sie bitte andere Services wie SMS und Mobile Data geistig auszublenden. Für Sprachtelefonie werden auf den folgenden Seiten drei Tarife unterschieden:

- Pay-Per-Use = Nutzungsabhängiges Entgelt (Euro pro Minute) mit oder ohne monatlicher Grundgebühr (beinhaltet auch Tarife mit sogenanntem Kostenschutz /-airbag). Bspw. "11 Cent pro Minute in alle Netze ohne monatliche Grundgebühr". D.h. die Kosten pro Monat variieren abhängig von der Nutzungsintensität. Bei Nicht-Nutzung liegen sie bei 0 - bei starker Nutzung steigen sie beliebig an.
- Volumenpaket = Monatliches Kontingent an Freiminuten zu festem Preis (Euro pauschal), darüber hinaus wird meist nutzungsabhängig abgerechnet. Bspw. "120 Freiminuten in alle Netze für 9 Euro monatliche Gebühr, danach 9 cent pro Minute". D.h. die Kosten pro Monat liegen bei mindestens 9 Euro und können ggf. steigen, wenn die 120 Freiminuten ausgereizt sind.
- Flat-Rate = Unberentztes Telefonieren zu festem Preis (Euro pauschal). Bspw. "Flat-Rate in alle Netze für 40 Euro pro Monat". D.h. egal wie viel telefoniert wird, die Kosten liegen fix bei 40 Euro pro Monat.

Die Daten werden im Rahmen einer Dissertation erhoben und dienen der wissenschaftlichen Forschung. Alle Antworten sind anonym – es gibt keine richtigen oder falschen Antworten. Antworten Sie bitte spontan und ohne langes Überlegen. Die Bearbeitung des Fragebogens dauert ca. 8 Minuten.

Soziodemographische Daten

Bitte nennen Sie uns Ihr Alter: _____

Was ist Ihr Geschlecht? Männlich Weiblich

Bitte geben Sie das ungefähres monatliche Bruttoeinkommen Ihres Haushalts an

- unter 1.500 EUR
- 1.500 bis 2.499 EUR
- 2.500 bis 3.499 EUR
- 3.500 bis 4.499 EUR
- 4.500 bis 5.499 EUR
- 5.500 bis 6.499 EUR
- 6.500 bis 7.499EUR
- 7.500 EUR oder mehr

Was ist Ihr höchster Bildungsabschluss?

- Kein Schulabschluss
- Volks- / Hauptschulabschluss
- Mittlere Reife / Realschule
- Abitur oder Fachhochschulreife
- Universitäts- oder Fachholschulabschluss
- Promotion / Habilitation

Haben Sie einen Mobilfunkvertrag?
(Antworten Sie bitte mit nein, wenn Sie eine Pre-Paid Karte nutzen, oder die Rechnung von einer anderen Person/Firma bezahlt wird.)

- Ja
- Nein

Bei welchem Mobilfunkanbieter?

- 1&1
- Base
- Blau
- Deutsche Telekom / T-Mobile
- Deutschland SIM
- Drillisch
- E-Plus
- Fonic
- Lidl
- Mobilcom
- O2
- Phonex
- Prima
- Simyo
- Vodafone
- Andere: _____

Bitte wählen Sie Ihren Tarif für Sprachtelefonie aus:
(Unabhängig davon, ob SMS oder Datennutzung inkludiert ist)

- Pay-Per-Use: Nutzungsabhängiges Entgelt mit/ohne Grundgebühr (beinhaltet Tarife mit Kostenschutz-/airbag)
- Volumenpaket: Monatliches Kontingent an Freiminuten, danach nutzungsabhängiges Entgelt
- Flat-Rate ins eigene Netz und ins Deutsche Festnetz, nutzungsbasiertes Entgelt für alle anderen Gespräche
- Flat-Rate in alle Deutschen Netze inkl. Festnetz

Geben Sie bitte den Namen Ihres Mobilfunktarifs ein (Falls Sie die genaue Bezeichnung nicht kennen, umschreiben Sie den Tarif bitte oder lassen das Feld leer):

Bitte geben Sie grob in Euro Ihre monatlichen Ausgaben für Mobiltelefonie an:

- Wie hoch ist Ihre gesamte Mobilfunkrechnung im Durchschnitt: _____
- Wie hoch ist die Gebühr für Ihre Flat-Rate / Ihr Volumenpaket für Sprachtelefonie: _____
(0, falls Sie keine Flat-Rate / kein Volumenpaket haben)

Reale Kunden

Wissenschaftliche Untersuchungen haben ergeben, dass einige Kunden Ihre Flat-Rate / Ihr Volumenpaket nicht ausnutzen und im Vergleich zu Pay-Per-Use mehr zahlen...

Ab wieviel Euro Preisersparnis pro Monat durch einen Tarifwechsel zu Pay-Per-Use bei Ihrem Anbieter würden Sie die Vorteile Ihrer Flat-Rate / Ihres Volumenpakets aufgeben und zu Pay-Per-Use wechseln? Gehen Sie davon aus, dass ein Tarifwechsel jederzeit möglich ist und keine zusätzlichen Kosten verursacht. Bitte geben Sie ganz-zahlige Euro Beträge ein.

- Bis zu welcher Preisdifferenz würden Sie noch auf keinen Fall an einen Tarifwechsel _____ denken?
- Ab welchem Betrag würden Sie anfangen, über einen Tarifwechsel nachzudenken? _____
- Bis zu welcher Preisdifferenz wäre das Beibehalten der Flat-Rate gerade noch vorstellbar? _____
- Ab welcher Preisdifferenz würden Sie auf jeden Fall den Tarif wechseln? _____

Ab wieviel Euro Preisersparnis pro Monat durch einen Wechsel zu Pay-Per-Use bei der Konkurrenz würden Sie Ihren Provider verlassen, die Vorteile Ihrer Flat-Rate / Ihres Volumenpakets aufgeben und zu Pay-Per-Use bei einem günstigeren Anbieter wechseln? Gehen Sie davon aus, dass ein Provider Wechsel zum übernächsten Monat möglich ist,

Sie gegen eine geringe Gebühr Ihre Rufnummer behalten können und Ihre Erreichbarkeit am Telefon für maximal einen Tag eingeschränkt ist. Bitte geben Sie ganz-zahlige Euro Beträge ein.

- Bis zu welcher Preisdifferenz würden Sie noch auf keinen Fall an einen Providerwechsel denken?

- Ab welchem Betrag würden Sie anfangen, über einen Providerwechsel nachzudenken?

- Bis zu welcher Preisdifferenz wäre das Beibehalten des aktuellen Providers gerade noch vorstellbar?

- Ab welcher Preisdifferenz würden Sie auf jeden Fall den Provider wechseln?

Hypothetisches Szenario PrimeTel

Im Folgenden geht es um ein hypothetisches Szenario: Sie sind Kunde von PRIMETEL!

Bitte denken Sie bei der Beantwortung aller kommenden Fragen nicht an Ihren eigenen Mobilfunkanbieter, sondern stellen Sie sich vor, Kunde des Mobilfunkanbieters PRIMETEL zu sein:

PRIMETEL ist ein Premium Anbieter. D.h. PRIMETEL bietet höchste Sprachqualität und Erreichbarkeit bei 100% Netzabdeckung und bestem Kundenservice. Ihr Tarif bei PRIMETEL ist eine Flat-Rate in alle Deutschen Netze zu einem monatlichen Preis von 80 Euro. Egal wie viel Sie Ihr Handy nutzen, Sie zahlen immer 80 Euro.

Wissenschaftliche Untersuchungen haben ergeben, dass einige Kunden Ihre Flat-Rate nicht ausnutzen und im Vergleich zu Pay-Per-Use mehr zahlen... Ab wieviel Euro Preisersparnis pro Monat durch einen Tarifwechsel von der Flat-Rate zu Pay-Per-Use innerhalb des Providers PRIMETEL würden Sie die Vorteile der Flat-Rate aufgeben und zu Pay-Per-Use wechseln? Gehen Sie davon aus, dass ein Tarifwechsel jederzeit möglich ist und keine zusätzlichen Kosten verursacht. Bitte geben Sie ganz-zahlige Euro Beträge ein.

- Bis zu welcher Preisdifferenz würden Sie noch auf keinen Fall an einen Tarifwechsel denken?

- Ab welchem Betrag würden Sie anfangen, über einen Tarifwechsel nachzudenken?

- Bis zu welcher Preisdifferenz wäre das Beibehalten der Flat-Rate gerade noch vorstellbar?

- Ab welcher Preisdifferenz würden Sie auf jeden Fall den Tarif wechseln?

Ab wieviel Euro Preisersparnis pro Monat durch einen Wechsel von der Flat-Rate zu Pay-Per-Use bei der Konkurrenz würden Sie den Provider PRIMETEL verlassen, die Vorteile der Flat-Rate aufgeben und zu Pay-Per-Use bei einem günstigeren Anbieter wechseln? Gehen Sie davon aus, dass ein Provider Wechsel zum übernächsten Monat möglich ist, Sie gegen eine geringe Gebühr Ihre Rufnummer behalten können und Ihre Erreichbarkeit am Telefon für maximal einen Tag eingeschränkt ist. Bitte geben Sie ganz-zahlige Euro Beträge ein.

- Bis zu welcher Preisdifferenz würden Sie noch auf keinen Fall an einen Providerwechsel denken?

- Ab welchem Betrag würden Sie anfangen, über einen Providerwechsel nachzudenken?

- Bis zu welcher Preisdifferenz wäre das Beibehalten des aktuellen Providers gerade noch vorstellbar?

- Ab welcher Preisdifferenz würden Sie auf jeden Fall den Provider wechseln?

Hypothetisches Szenario GünsTel

Im Folgenden geht es um ein hypothetisches Szenario: Sie sind Kunde von GÜNSTEL!

Bitte denken Sie bei der Beantwortung aller kommenden Fragen nicht an Ihren eigenen Mobilfunkanbieter, sondern stellen Sie sich vor, Kunde des Mobilfunkanbieters GÜNSTEL zu sein: GÜNSTEL ist ein low-cost Anbieter. D.h. es gibt keine Ladengeschäft und der Service ist ausschließlich online oder telefonisch zu erreichen. Die Sprachqualität ist ausreichend und Netzabdeckung ist in 90% von Deutschland vorhanden. Ihr Tarif bei GÜNSTEL ist eine Flat-Rate in alle Deutschen Netze zu einem monatlichen Preis von 40 Euro. Egal wie viel Sie Ihr Handy nutzen, Sie zahlen immer 40 Euro

Wissenschaftliche Untersuchungen haben ergeben, dass einige Kunden Ihre Flat-Rate nicht ausnutzen und im Vergleich zu Pay-Per-Use mehr zahlen... Ab wieviel Euro Preisersparnis pro Monat durch einen Tarifwechsel von der Flat-Rate zu Pay-Per-Use innerhalb des Providers GÜNSTEL würden Sie die Vorteile der Flat-Rate aufgeben und zu Pay-Per-Use wechseln? Gehen Sie davon aus, dass ein Tarifwechsel jederzeit möglich ist und keine zusätzlichen Kosten verursacht. Bitte geben Sie ganz-zahlige Euro Beträge ein.

- Bis zu welcher Preisdifferenz würden Sie noch auf keinen Fall an einen Tarifwechsel denken?

- Ab welchem Betrag würden Sie anfangen, über einen Tarifwechsel nachzudenken?

- Bis zu welcher Preisdifferenz wäre das Beibehalten der Flat-Rate gerade noch vorstellbar?

- Ab welcher Preisdifferenz würden Sie auf jeden Fall den Tarif wechseln?

Ab wieviel Euro Preisersparnis pro Monat durch einen Wechsel von der Flat-Rate zu Pay-Per-Use bei der Konkurrenz würden Sie den Provider GÜNSTEL verlassen, die Vorteile der Flat-Rate aufgeben und zu Pay-Per-Use bei einem günstigeren Anbieter wechseln? Gehen Sie davon aus, dass ein Provider Wechsel zum übernächsten Monat möglich ist, Sie gegen eine geringe Gebühr Ihre Rufnummer behalten können und Ihre Erreichbarkeit am Telefon für maximal einen Tag eingeschränkt ist. Bitte geben Sie ganz-zahlige Euro Beträge ein.

- Bis zu welcher Preisdifferenz würden Sie noch auf keinen Fall an einen Providerwechsel denken?

- Ab welchem Betrag würden Sie anfangen, über einen Providerwechsel nachzudenken?

- Bis zu welcher Preisdifferenz wäre das Beibehalten des aktuellen Providers gerade noch vorstellbar?

- Ab welcher Preisdifferenz würden Sie auf jeden Fall den Provider wechseln?
