DRIVERS OF CONSUMER BEHAVIOR AND COMPETITIVE STRATEGY OUTCOMES – PLURALITY OF PERSPECTIVES, MODELING, AND EMPIRICAL EVIDENCE

Inauguraldissertation
zur Erlangung des akademischen Grades eines
Doktors der Wirtschaftswissenschaften durch die
Wirtschaftswissenschaftliche Fakultät
der Westfälischen Wilhelms-Universität Münster

WESTFÄLISCHE
WILHELMS-UNIVERSITÄT
MÜNSTER

vorgelegt von
JAN PIENING
aus Eckernförde

Münster, 2013

Erster Berichterstatter: Prof. Dr. Thomas Ehrmann

Zweiter Berichterstatter: Prof. Dr. Jens Leker

Dekan: Prof. Dr. Christoph Watrin

Tag der mündlichen Prüfung: 24. April 2013

Acknowledgements

I would like to express my deep gratitude to my dissertation advisor, Professor Dr. Thomas Ehrmann, for his patient guidance, extensive expertise and invaluable advice. His sincere trust and confidence, his continuous support and his profound sense of humor provided a fruitful environment for research and teaching. My grateful thanks are extended to Prof. Dr. Jens Leker for his co-supervisory of my thesis and Prof. Dr. Martin Bohl for joining the dissertation committee. I also thank Dr. Brinja Meiseberg, Alfred Koch and Jochen Lengers for being great colleagues. Innumerable life-enhancing discussions made the process of working on this dissertation an important and unforgettable time for me.

Finally, I wish to thank my family, particularly my parents Ingrid and Jochen Piening, and Charlotte Jestaedt for their support, encouragement and patience.

TABLE OF CONTENTS

PART B

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

asf.	and so forth
BC	BahnCard
CCDF	complementary cumulative distribution function
CDF	cumulative distribution function
CIF	cumulative incidence function
coef.	coefficient
conf. interval	confidence interval
CRM	customer relationship management
DB	Deutsche Bahn
e.g.	exempli gratia
et al.	et alii
etc.	et cetera
et seq.	et sequens
HMO	health maintenance organization
i.e.	id est
obs.	observations
p.	page
pp.	pages
PoS	point of sale
PoU	point of usage
ROC	receiver operating characteristic
std. err.	standard error
vs.	versus

PART A

I. Economic Principles and Trends, Firm Performance and Consumer Behavior in the Light of Technological Market Change

"All truth passes through three stages. First, it is ridiculed. Second, it is violently opposed. Third, it is accepted as being self-evident."
Arthur Schopenhauer (1788-1860)

Any economic principle, the success of firms, the outcomes of strategies, customer needs and activities are more or less affected by the concept of *uncertainty*.

In this connection, Akerlof's (1970) essay "Market for Lemons: Quality Uncertainty and the Market Mechanism"[1] is one of the most respected essays in economics, and has profoundly influenced economic thinking in virtually every field of economics (from industrial organization and public finance to macroeconomics and contract theory).

His paper uses the market for used cars as an example of the problem of *quality uncertainty*. There are good used cars and defective used cars ('lemons'), normally as a consequence of several not-always-traceable variables such as the owner's accident history, quality and frequency of maintenance and driving style. Because a buyer of a used car cannot beforehand (free of charge, if at all) assess its quality, her 'best guess' for a given car is that the car is of average quality and accordingly, she will be willing to pay only the price of a car of known average quality for it. This means that the owner of a good used (i.e., carefully maintained, never-abused) car will be unable to get a high enough price to make selling that car worthwhile.

[1] A lemon is an American slang term for a car that is found to be defective only after it has been bought.

Therefore, owners of good cars will not place their cars on the used car market. The withdrawal of good cars reduces the average quality of cars on the market, causing buyers to revise their expectations for any given car downward. This, in turn, motivates the owners of moderately good cars not to sell, and so on. As a result, suppliers of high-quality cars are driven out of the market.

Consequently, *asymmetric information* seems to play a key role, potentially affecting any market where the quality of goods would be difficult to see by anything other than casual inspection (e.g., market for cars, market for education, insurance markets, market for loans, art markets, etc.). To prevent a *market failure* according to this simple model framework, the information asymmetry has to be eliminated or reduced which involves further costs (i.e., through seals of approval or quality, or independent experts). Applied to works of art, the mediating role of galleries as experts prevents the art market to fail. How (mediating) firms evolve *competitive success* in markets with high quality uncertainty is subject to chapter IV (Part B).

In this context, Williamson (1975) famously analyzes transactional variables (e.g., bounded rationality, uncertainty, asymmetry in information), which help govern the mode and performance of organizations. It explores the formation, evolution, and operation of organizations, especially hierarchical ones, and markets. All of this is called by Williamson an "organizational failure framework": Organizational or market development depends upon *failures traced to transactional factors*. This framework copes with questions of structure, of size, of technology, and of decision making *in* organizations.[2] *Outside* organizations, a strategic concept on *competitive forces* governing competition in an industry has essentially shaped economic thinking: for nearly three decades, the ideas of Porter (1980, 1985) have been highly influential to our understanding of the way in which firms compete. Particularly, the concepts of differentiation and cost leadership have had an immense impact on business practice and research (Besanko et al. 2010; Grant 2010). Porter and others (e.g., Barney 1997; Mintzberg and Quinn 1988; Tirole 1988) assert, and empirical evidence supports (e.g., Dess and Davis 1984; Kotha and Vadlamani

[2] In this connection, it may be referred to Podolny (1994) who points to the importance of social structure in providing the framework within which organizational actors economize on transactions.

1995; Miller and Dess 1993; Miller and Friesen 1986a, 1986b; Phillips, Chang, and Buzzell 1983; Teece, Pisano, and Shuen 1997), that differentiation and cost leadership are fundamental to business strategy and that these foci can be linked to *business success*.

Virtually following in the footsteps of the Porter tradition, a different economic camp advocating *customer relationship management* (CRM) has emerged. In a metaphorical sense, a "revolution" (Winer 2001) or rather "explosion" (Payne and Frow 2005) of CRM has considerably changed the strategic alignment of many companies. With the Internet and other telecommunication innovations drawing us ever closer to the economist's concept of a perfect market, many products and services are increasingly perceived more like commodities (Srinivasan, Anderson, and Ponnavolu 2002). In this context, the essence of the information technology revolution constitutes the opportunity to build better relationships with customers than has been previously possible in the offline world (Gupta and Aggarwal 2012). By combining the abilities to respond directly to customer requests and to provide the customer with a highly interactive, customized experience, companies have considerably improved preconditions and ability today to establish, nurture, and sustain long-term customer relationships than ever before. The ultimate goal is to transform these relationships into greater profitability by increasing repeat purchase rates and *reducing customer acquisition costs*.

Allowing for the preconditions of these considerations, Brynjolfsson and Mendelson (1993) note that the structure of the *organization's information system* is a key element of organizational transformation.[3] In this regard, Jensen and Meckling (1992) represent the structure of organizations as an efficient response to the structure of their *information costs*. Accordingly, a change

---

[3] They argue that new technologies allow managers to handle more functions and widen their span of control. Fewer levels of management hierarchy are required, enabling companies to flatten the pyramid of today's management structure. Moreover, the new information technologies allow decentralization of decision-making without loss of management awareness; thus employees at all levels can be encouraged to be more creative and intrapreneurial. Hence, the organizational structures are said to become more flexible, more responsive, and ultimately result in higher quality.

The firm and the market have each been frequently modeled as primarily information processing institutions (Galbraith 1977; Hayek 1945). At this point, it may also be referred to Miles et al. (1978), who propose a well-reputed theoretical framework dealing with alternative ways in which organizations define their product-market domains (strategy) and construct mechanisms (structures and processes) to pursue adaption strategies.

in information costs must induce a change in organizational structure. In particular, IT has changed the costs of processing and transferring certain types of information (e.g., quantitative data). Using the Jensen-Meckling terminology, different network participants can make more effective use of their specific knowledge when the costs of transferring and processing general knowledge are reduced. Furthermore, technology enables the development of markets that, by their very nature, transform specific knowledge into general knowledge. In other words, the reasons for the recent hype on CRM come out more basic: they are of a strategic nature, being *cost-induced by the IT development*. The latter changes the interaction of competitive forces and particularly builds the basis for any customer relationship concept.

Yet, there is no uniform definition in the literature: the concepts of CRM vary from narrow perspectives associated with technology, as Kutner and Cripps (1997) simply put it as “data-driven marketing”, to strategic and holistic approaches. From the latter viewpoint, CRM is not simply an IT solution that is used to acquire and grow a customer base, but involves a profound synthesis of strategic vision, a corporate understanding of the nature of customer value in a multichannel environment as well as the utilization of the appropriate information management and CRM applications, and high-quality operations, fulfillment, and service (Payne and Frow 2005). Thereby, the necessity of a cross-functional integration of processes, people, operations, and capabilities has to be pointed out.

A strategy development process requires a dual focus on the organization’s business strategy and its customer strategy (Payne and Frow 2005). These perspectives are reflected in the findings by Reimann, Schilke, and Thomas (2010) that CRM enhances the business strategy of cost leadership (firm perspective) and drives firms’ differentiation efforts, particularly in highly commoditized industries (customer perspective). Recent research on this subject has emphasized that both differentiation and cost leadership strategies have a positive impact on performance (Acquaah and Yasai-Ardekani 2008), thus confirming the *impact of CRM on firm achievements* (i.e., enhanced strategic position in the market and improved performance outcomes).

Several studies highlight the need to understand the mechanisms and conditions that influence *how* and *when* CRM affects firm success (e.g., Reimann, Schilke, and Thomas 2010; Shugan 2005; Zablah, Bellenger, and Johnston 2004).

The variety of economic methods and models is immense. One central approach to the above-mentioned issue is *data mining* (also called 'knowledge discovery in databases') which combines tools from statistics and artificial intelligence and describes the process of discovering interesting and useful patterns and relationships in large volumes of data (Clifton 2013). The application of data mining tools in CRM is an emerging trend in the global economy. Analyzing and understanding customer behaviors and characteristics is the foundation of the development of a competitive CRM strategy, so as to acquire and retain potential customers and maximize customer value. In this connection, *loyalty programs* are critical CRM tools used to identify, reward, and successfully retain profitable customers. Chapters I-III (Part B) of this work give a deeper introduction into strategic and methodological aspects of this tool by analyzing and discussing their design, effectiveness and performance implications. Chapter IV (Part B) focuses on market-level performance.

In a nutshell, this thesis will have a closer look on different aspects of the *drivers of consumer behavior* and *competitive strategy outcomes*, thereby considering the general issues of 1) the growth of e-commerce (Chapter I, Part B), 2) the significance of CRM strategy conception and performance (Chapter II and III, Part B), and 3) the comprehension of evolutionary market dynamics (Chapter IV, Part B). In the course of the different chapters, we adopt different approaches and perspectives which are aimed at bringing this topic area down to a round figure. The studies hold conceptional and strategic implications for the effective design of CRM processes and strategies, and for the success in two-sided markets.

The increased penetration of CRM philosophies and strategies in organizations can help to improve how firms work to establish valuable long-term relationships with their customers, i.e. obtain sustainable market success. This work extends a managerial perspective that stresses the importance of cross-functional processes in (CRM) strategy and market evolution.

The next section summarizes the four main chapters of this dissertation, elaborates the specific research questions and illustrates the contributions to the literature.

II. SUMMARY OF CHAPTERS AND CONTRIBUTION TO THE LITERATURE

1. Do Online Customers Make Better Purchases? – An Analysis of Point of Sale Choice and its Linkages to Customer Loyalty and the (Ir)Rationality of Buying Decisions

Over the last decade (retailing and service-oriented) firms have increasingly been utilizing electronic distribution strategies to augment their physical infrastructure and sustain their competitive capacity (Bauer, Grether, and Leach 2002; de Vries 2006; Gunasekaran, Lai, and Cheng 2008; Flavián and Guinalíu 2005; Hitt and Frei 2002). In this context, the outstanding success of pure online-business models (e.g., Amazon or Zalando) has considerably raised competition and changed the expectation and shopping behavior of consumers (Darley and Blankson 2010; Park, Lee, and Han 2007; Srinivasan, Anderson, and Ponnavolu 2002). Besides the fact that an attractive Internet presence has become a 'compulsory standard', electronic commerce has considerably grown (Pavlou and Fygenson 2006). Consequently, firms of the retailing and service sector have increasingly transitioned to hybrid models integrating traditional and online distribution (Levary and Mathieu 2000; Yao and Liu 2005). Hence, understanding the relevance of either channel, thereby incorporating their interdependency as well as leveraging their performance has become a pivotal challenge for strategists of all kinds of firms (Ritchie and Brindley 2007; Wallace, Giese, and Johnson 2004; Webb 2002). In this context, especially the (general) assessment of the value of loyalty programs, and therefore, profound knowledge about conditions and drivers of customer loyalty across distribution channels could help them to define and achieve competitive targets more effectively.

Accordingly, this chapter examines the linkages between point of sale and consumers' purchase behavior. First, we investigate consumer-inherent and contingent factors that drive customers' point of sale choice. Second, adopting a consumer perspective, we study whether online purchases or counter purchases tend to yield higher purchase decision quality. We establish whether such linkages hold across different customer segments and pricing contexts, and we also examine consumers' (collective) learning effects in terms of improving on decision quality over time. Third, moving on to the firm perspective, we study subsequent customer loyalty in either distribution channel, and explore how loyalty develops across different segments, pricing contexts, and levels of decision quality.

Based on data from a customer loyalty program in the railway service, comprising more than four million transactions of over 300,000 customers, the study results show how various consumer-inherent and contingent factors affect point of sale choice. Contrary to our expectations, the rationality of purchase decisions is in fact dependent on the chosen point of sale. Besides, it largely varies across customer segments. However, learning effects do occur over time, yet their strength differs across low- and high-price contexts as well as across consumer groups. Loyalty depends on both pricing contexts and segments as well as on customers' previous decision quality and point of sale choice. In particular, the empirical results provide practical implications for CRM strategy and implementation.

The contribution of the first chapter is the following:

- First, there is a lack of research into customer characteristics that drive the use of online purchase systems versus traditional channels, and the question of how different channels affect customer behavior and customer loyalty remains surprisingly unanswered to date (Brown and Dant 2009; Hitt and Frei 2002; Homburg, Hoyer, and Fassnacht 2002; Wallace, Giese, and Johnson 2004). Thus, research has not adequately considered market-level responses to retailing through online versus offline distribution, although this is of essential importance to researchers as well as practitioners. Therefore, the study sheds some light on the drivers of point of sale choices.

- Second, previous studies on two-part pricing systems primarily focus on rather technical and game-theoretical aspects (e.g., Feldstein 1972; Hayes 1987; Oi 1971; Yin 2004), pricing and promotional issues (e.g., Gijsbrechts 1993; MacKie-Mason and Varian 1995; Murphy 1977) or flat-rate biases (e.g., Della Vigna and Malmendier 2006; Goettler and Clay 2011; Lambrecht and Skiera 2006; Schmale, Ehrmann and Dilger 2013). But obviously, there is a lack of research into two-part pricing systems across distribution channels (Grewal and Levy 2009), although such pricing schemes are increasingly used in services and are particularly intended to create customer loyalty. This study is aimed to fill this gap.

- Third, we can also offer some insights into potential benefits of a critical re-evaluation of individual purchase behavior and of learning effects in the railway service sector, which might be generalized to various other contexts where both online and offline distribution are the norm (e.g., online vs. offline travel bookings, hotels, rental cars).

- Fourth, customer loyalty is often managed at the aggregate customer level with relatively low or no differentiation across the entire customer base. Thus, individual customer level differences (psychographic, demographic, behavioral, attitudinal and so on) may be ignored. Kumar and Shah (2004) indicate the necessity of rectifying some fundamental level problems prevalent with the way customer loyalty is managed and interpreted by companies. This study extends research on distribution channel performance, providing a segment-specific approach.

- Additionally, few studies have focused on how customer heterogeneity is related to online versus offline distribution (Hitt and Frei 2002; Tsai and Lee 2009). Directing attention to the question, of “what factors influence a consumer’s choice of the Internet versus conventional channel”, Grewal and Levy (2007) point this issue out as another major research gap.

Thereby, this chapter offers managerial implications to both strategy and customer relationship management, for how the (segment-specific) configuration of two-part tariff systems can enhance performance, by exploring these specific gaps in the literature from (1) a descriptive, as well as from (2) consumer and (3) firm perspective:

1. What factors influence a consumer’s choice of the Internet versus a conventional channel?

2. Does either type of distribution channel tend to yield ‘better’ results in terms of consumers’ purchase decision quality? Do potential linkages apply across consumer segments and pricing contexts alike? Can consumers realize learning effects that enhance their decision quality over time, and if so, what conditions accelerate or hamper those learning effects?

3. How loyal are customers who choose online channels compared with those preferring counter purchase? How are different consumer segments, pricing contexts and levels of individual decision quality related to loyalty?

2. Competing Risks for Train Tickets – An Empirical Investigation of Customer Behavior and Performance in the Railway Industry

Understanding how firms can profit from their customer relationships is highly important for academics and practitioners (Boulding et al. 2005; Payne and Frow 2005). Customer relationship management (CRM) can be characterized as an organizational capability having the potential to be a source of competitive advantage, which in turn permits firms to improve their positioning and ultimately enhance their performance (Day 2004; Hogan, Lemon, and Rust 2002; Mithas, Krishnan, and Fornell 2005). In this connection, Reimann, Schilke, and Thomas (2010) establish the link between CRM and business strategies and develop our theoretical understanding of the process by which CRM contributes to an organization's success.

Particularly, previous research has also stressed the need to generate further insights into the outcomes of CRM practices in the transportation sector, and towards opportunities for influencing consumer choices more effectively (Ellinger, Daugherty, and Gustin 1997; Ellinger, Daugherty, and Plair 1999; Ramanathan 2010; Steven, Dong, and Dresner 2012). Additionally, Zablah, Bellenger, and Johnston (2004) argue that mechanisms through which CRM enhances performance are not well understood, and therefore managers have little (conceptual) guidance on how to focus their CRM efforts. Shugan (2005) claims that more research is needed to isolate and fully understand the generative mechanisms through which CRM affects a firm's performance.

Accordingly, drawing on previous work in transportation research (Daugherty et al. 2009; Ellinger, Daugherty, and Plair 1999; Grawe, Daugherty, and Dant 2012; Ramanathan 2010; Steven, Dong, and Dresner 2012), this study is the first that uses competing risks models to analyze consumers' choices, and particularly subsequent changes, of two-part pricing contracts that enable railway customers to travel at discount prices for an up-front fee during the contract period. Based on large-scale, unique loyalty program data comprised of more than four million individual transactions of German railway customers, comprehensive travel history data spanning a timeframe of almost six years is arranged within a competing risks framework. Based on a semi-parametric proportional hazards model stratified by failure type we simultaneously estimate effects on three types of contractual events: cancellation, upgrade, and downgrade of a loyalty card (‘BahnCard’). Focusing on CRM practices, we find several relevant factors, some of which railway companies can influence to their advantage. For example, installing auto-renewal procedures for loyalty cards decreases cancellation risks, automated electronic mailings (e.g., reminders and account statements) and advertising (e.g., ticket offers) can be counterproductive and increase the risk of cancellation. A better understanding of these key drivers is essential when discussing the effectiveness of CRM practices, especially in the context of customer loyalty programs, and if proposing business strategies matched to future market development in the transportation sector.

This chapter seeks to provide new theoretical insights by integrating previous research on CRM and two-part pricing schemes for the transportation sector. Our results offer practical implications for transportation companies and other service sectors, e.g., concerning the creation and management of customer programs when using two-part pricing schemes, and provide performance and policy implications for suppliers of comparable transportation services as well as strategic impulses for firms applying two-part pricing schemes in general.

The contribution of the second chapter is the following:

- First, it adds to the recent literature on transportation and logistics management that emphasizes the growing need for customer orientation and relationship management (e.g., Ganesan et al., 2009; Grawe, Daugherty, and Dant 2012; Ramanathan 2010; Steven, Dong, and Dresner 2012) by systematically exploring how such approaches can be managed in practice, as well as by highlighting their specific effects on (un)desired business outcomes in the context of rail travel.

- Second, little empirical evidence links program participation with actual loyalty and firm performance. Besides, the drivers of loyalty remain predominantly elusive (McCall and Voorhees 2010). This chapter investigates such drivers in a railway-setting and discusses corresponding performance implications, particularly, concerning the creation and management of customer loyalty programs and customer relationship management practices when using two-part pricing schemes.

- Third, there is little research into consumers' contract choices and travel behavior in the context of two-part pricing schemes, although these are commonly used in railway transportation as well as other sectors. As a consequence, a comprehensive approach towards understanding customers' travel behavior and particularly, the determinants of their contractual choices and changes therein, is lacking in the literature on (rail) transportation settings. The same applies to the question how such decisions can be influenced effectively.

- Fourth, we extend the conventional cancellation risks framework by applying competing risks models to the specific context of customer loyalty cards, which provides a broader perspective on customer retention in the railway sector. Our method has not been transferred to transportation studies on consumer travel behavior before. Based on this unconventional methodological approach (see also, Li et al. 2012; Smith 2012; Wen, Wang, and Fu 2012, for recent methodological contributions in the rail sector), our results would help transportation firms assess the potential effects of promoting, re-developing, and fine-tuning their two-part pricing schemes on consumers' subsequent contractual choices and usage decisions, both initially and over an extended period.

- Additionally, the awareness of the need to improve our understanding of the outcomes of CRM practices in the transportation sector and also of the resulting opportunities to influence consumer choices more effectively has grown considerably in recent years (see Ellinger, Daugherty, and Gustin 1997; Ellinger, Daugherty, and Plair 1999; Ramanathan 2010; Steven, Dong, and Dresner 2012, on various aspects of customer services and loyalty in logistics and transportation settings). We point out some systemic flaws in one of the biggest loyalty programs in Germany, and highlight some critical leverage points relevant to improving the effectiveness of loyalty programs in rail travel.

Thereby, this chapter offers managerial implications for how to assess the key drivers in loyalty programs, by exploring these specific gaps in the literature:

1. What determines contractual choices of customers? How can these choices be influenced effectively?

2. What key drivers ensure the effectiveness of loyalty programs?

3. How can such approaches be managed in practice, and which specific effects on (un)desired business outcomes are entailed in the context of rail travel?

3. Learning Effects in Loyalty Programs: Performance Impacts of Decision-Making Behavior and Pricing

Recent years have witnessed a steep increase in company investments in customer relationship management (CRM) strategies. In particular, loyalty programs have been among the most frequently used forms of CRM efforts in many industries (Kim et al. 2009). The success of customer loyalty programs enhances customer retention. Its success depends on how consumers accept and use their corresponding loyalty cards: From firm perspective, existing academic research demonstrated the rationale behind loyalty program adoptions theoretically (Kim, Shi, and Srinivasan 2001; Zhang, Krishna, and Dhar 2000), and provided empirical evidence for their effectiveness (Bolton, Kannan, and Bramlett 2000; Leenheer et al. 2007; Lewis 2004; Mägi 2003). Yet, little research has examined customer perceptions concerning positive outcomes of loyalty programs (Mimouni-Chaabane and Volle 2010), and consumer adoption of loyalty cards, particularly consumer learning in loyalty programs, has not been explored in the literature at all.

Based on a comprehensive loyalty program data set of German railway customers, chapter III analyzes the structure of consumer learning and 'unlearning' curves[4] in low- and high-price contexts of railway services, and discovers whether learning and unlearning throughout loyalty card usage is characterized by an inverse relationship.

Further, this research illustrates the linkages of loyalty card usage, learning, and pricing issues to cancellation behavior, and highlights multiple effect changes over time. Using a sequential logit model, it is shown that learning effects and pricing strategies do have an impact on retention rates and their influence changes with ongoing contract duration.

For structuring customer loyalty programs, the implication for marketing managers is to consider behavior patterns as a result of tariff arrangements and to facilitate learning how to correctly use the loyalty cards, thus leading to associated higher retention rates.

[4] In this context, unlearning curves represent the development of those customer shares ceasing to use their loyalty card optimally, i.e. rationally.

The contribution of the third chapter is the following:

- First, this research adds to theory how customers learn in loyalty programs, and how behavioral aspects, particularly learning, and price structures affect customer loyalty. Thereby, it offers some results concerning the research gap emphasized by McCall and Vorhees (2010) who point out that despite the proliferation of loyalty programs, little empirical evidence links program participation with actual loyalty, and the drivers of loyalty remain elusive.

- Second, research has investigated the interrelationship between customer experience and churn rates. In this context, Jamal and Bucklin (2006) provide empirical evidence from satellite television industry. This study seeks to extend their finding concerning service experience in terms of usage, learning and unlearning to the railway sector, which are relevant most likely in various other customer loyalty program contexts, particularly in two-part tariff systems (e.g., airlines, car-sharing, hotels).

- Third, this research likewise complements a recent literature on choice and consumption under multi (two and more)-part tariffs (Ascarza, Lambrecht, and Vilcassim 2012; Bagh and Bhargava 2007; Grubb 2009; Grubb and Osborne 2012; Iyengar, Ansari, and Gupta 2007; Jensen 2006), which has so far abstracted from potential effects of the tariff structure on usage and customer retention.

- Fourth, our approach approves the concept of perceived price fairness (Bolton, Warlop, and Alba 2003; Xia, Monroe, and Cox 2004), at this, the result being consistent with prospect theory and mental accounting, which suggests that consumers tend to perceive multiple prices as more punishing than a single price of equal amount (Kahneman and Tversky 1979; Thaler 1985; Thaler and Johnson 1990). Besides, framing effects provide numerous opportunities to isolate important loyalty drivers while simultaneously evaluating the effectiveness of these, as indicated by McCall and Voorhees (2010), who also emphasize that more research is needed to better explain how the aggregate framing of a program affects consumer evaluations.

- Additionally, Grewal and Levy (2009) add to existing issues in e-tailing research, pointing on how to coordinate online and offline distribution channels in the context of two-part pricing systems. Our results provide explicit indication for differences in loyalty in different distribution channels of the railway setting and can help to develop sustainable CRM concepts and strategies.

Thereby, this chapter offers managerial implications for how to evaluate consumer learning in loyalty programs, by exploring these specific gaps in the literature:

1. How does consumer learning about (non-)optimal choices affect customer retention rates?

2. How relevant is an integrative treatment of usage, usage adoption (i.e., learning), and perceptional price policies and strategies in the development and application of customer retention concepts?

3. How do consumers' perceptions of prices affect loyal behavior?

4. The Success of Art Galleries: A Dynamic Model with Competition and Information Effects

Two-sided markets (or networks) can be found in many industries. Examples are manifold: video game consoles and credit cards, health maintenance organizations (HMOs) and operating (software) systems, communication networks (such as the Internet), the whole media industry and newspapers, the pay-tv market and scientific journals as well as the market for new works of art exhibit the economics of two-sided markets (Eisenmann, Parker, and van Alstyne 2006; Rochet and Tirole 2003). These are characterized by two sets of agents, e.g., patients and doctors, end-users and developers, consumers and advertisers, artists and art collectors, etc. who interact with each other via an intermediary or platform (e.g., hospital, software/media company, art gallery, etc. (Rysman 2009)). In this connection, the outcomes of the interaction are affected by the decisions of both sets of agents, i.e. by an (uninternalized) externality (Armstrong 2006; Rochet and Tirole 2006).

Since most two-sided markets are prone to quality uncertainty (on one or even both sides of the market), the crucial economic question is whether competition among intermediaries in two-sided markets plays a role for the outcome of the market process. From an economic perspective, the art market displays the pivotal problems of two-sided markets with high quality uncertainty and considerable innovation intensity. Uncertain subjective quality evaluations trigger the emergence of institutions in a market economy intended to reduce this uncertainty. Referring to this fact, a whole industry of experts has evolved, which helps to overcome quality uncertainty by actively evaluating and distributing information on works of art (Becker 1982; Caves 2000; Currid 2007). In a world centered on stardom and hits we assume that the glamorous business of arts should not only have superstars on the side of artists, but also winners on the side of galleries.

Building on Rosen's (1981) and Adler's (1985) central theories on star effects, this paper analyzes quantitatively whether superstar effects exist in this deep-pocket market[5] and if so, to find an adequate approximation of the underlying mechanism for the evolution of art galleries. Accordingly, we derive 'market success' of art galleries from annual rankings (*Kunstkompass*) of the world's most in-demand artists and generate art market data from the years 2001, 2004 and 2008. This ranking is formalized, connected to dynamic models of several specified processes from statistical physics, as well as interpreted economically, and finally empirically tested. The findings suggest that the success of art galleries depends strongly on information and innovation effects, but is hardly affected by competition effects. We find that the superstar effect in the case of galleries can be understood as an appropriation of search and entrance costs which emerge whenever consumption requires special knowledge and social inclusion.

The contribution of the fourth chapter is the following:

- First, Franck and Nüesch (2007) and Ehrmann, Meiseberg, and Ritz (2009) point out that the superstar effects are predominantly analyzed in mass markets, whereas deep-pocket markets like the market for art galleries are still hardly ever explored. So, the chapter extends the literature of superstar effects.

- Second, we take up ideas from statistical physics to model processes that allow us to analyze the development of different types of distributions of success in the market for art galleries. This way, we shed some light on the evolutionary dynamics of the success of art galleries, which can presumably be transferred to various other two-sided markets characterized by high quality uncertainty.

- Third, we apply new methods of empirical testing to determine which distribution best fits our data. Our data reveals lognormal distribution (as the consequence of a geometric Brownian motion) constituting the underlying stochastic process. By offering an economic meaning for this process, we hypothesize that the art marketing process is not in-

[5] A 'deep-pocket' market is characterized by the fact that a relatively small number of consumers are willing to pay a large premium to consume the services of the few 'best' performers.

herently rudderless, and we propose a reversed version of Baumol's (1986) assumption and suggest that the imperfection of the available information on prices and transactions does matter (in the sense that better information about the behavior of the market could help to make decisions more effectively).

- Additionally, we find that economic peculiarities may also be main drivers of the evolution of success. This is (not only) the case in cultural markets when quality uncertainty is high for the final customers, and when on the side of the intermediary platform specific investments are required to build up a sustainable reputation with both artists as well as art collectors and investors. Having established such a reputation, competition among intermediary platforms plays hardly any role. Again, it seems very likely that this result could be generalized for other two-sided markets with high quality uncertainty.

Thereby, this chapter gives heed to a more sophisticated understanding of the evolutionary dynamics of the success of galleries, and more generally, success in (two-sided) markets with high quality uncertainty, by exploring these specific gaps in the literature:

1. Do the economics of the gallery sector support the long-term success of individual actors?

2. How can a gallery that was successful in the past gain an ever increasing reputational advantage as an expert in the selection of future trends compared to less successful galleries?

3. What kind of dynamic economic process takes effect such that a small, inconsequential firm (here an art gallery) becomes dominant in a field?

III. INTEGRATIVE FRAMEWORK

The core of this dissertation contains four main chapters. These chapters are unified by the idea of analyzing the drivers of consumer behavior and market evolution through integrating a plurality of perspectives and (multidisciplinary) modeling approaches while placing particular emphasis on the concepts of customer life cycle, rationality of consumer decision-making and firm performance. Figure 1 illustrates the organization of chapters. By taking both the customer and the firm perspective into account, employing both static and dynamic models, as well as adopting segment-specific and generic longitudinal approaches, the research framework at hand extends the literature on CRM and market performance, and particularly sheds lights on customer-driven success factors and competitive strategy outcomes. As the chapters are modular in nature, they can be read solitarily according to individual foci of interest. Figure 2 provides a synopsis of research aims, methods and findings.

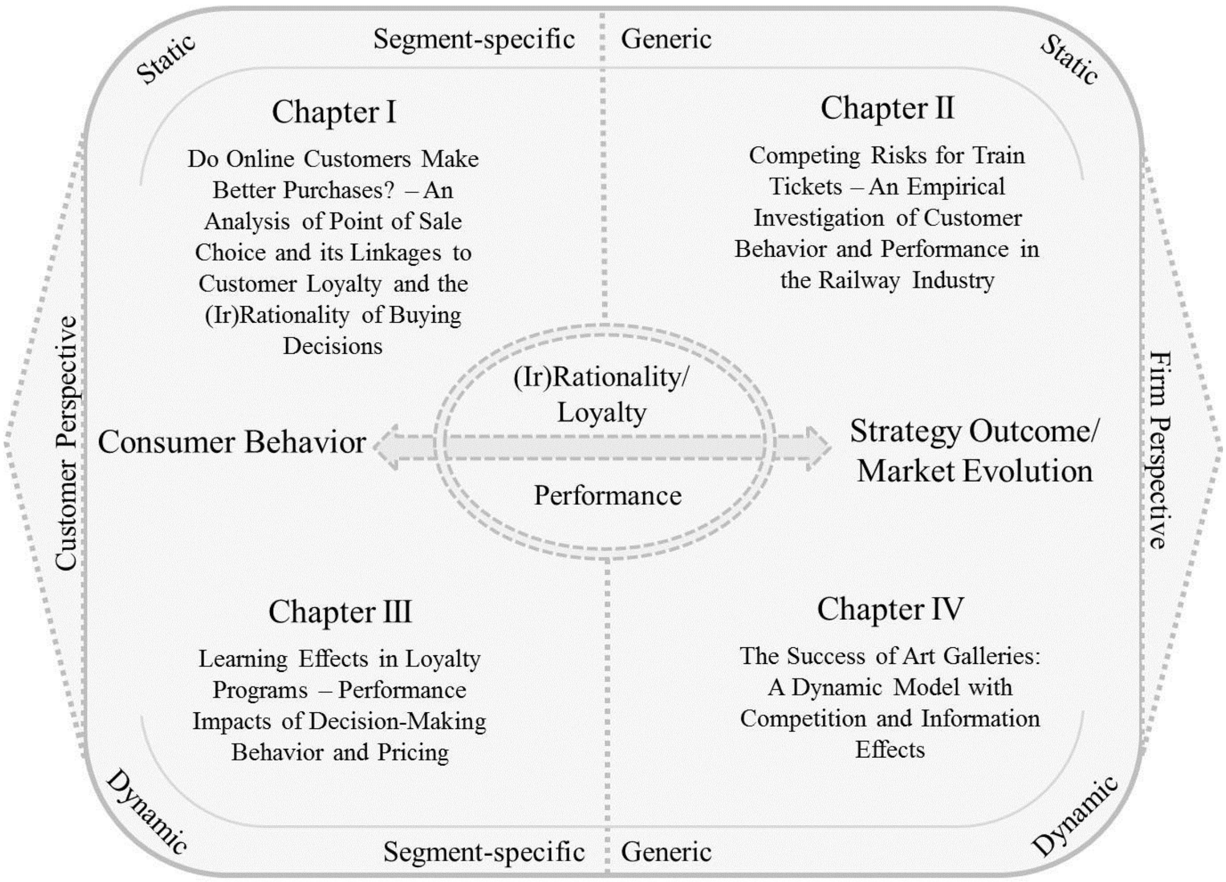


Figure 1. *Systematization of Chapters*

CUSTOMER-DRIVEN SUCCESS FACTORS AND COMPETITIVE STRATEGY OUTCOMES

	SEGMENT-SPECIFIC APPROACHES	GENERIC APPROACHES	
CUSTOMER PERSPECTIVE	**Chapter I** Do Online Customers Make Better Purchases? *Research Aim:* Providing empirical evidence of the drivers of customers' PoS choice (online vs. traditional channel) and its linkages to purchase behavior. *Methodological Approach:* Logistic regression model, chi-square, Fisher-Yates and t-tests; based on customer loyalty program data. *Results:* Customer heterogeneity affects outcomes of retail strategies that combine distribution channels, and is important for allocating resources effectively across/within channels; Despite opportunities for acquiring information relevant for purchase decisions at either PoS, decision quality is much higher in online channels; Contrary to what previous studies would predict, customer loyalty is higher in online channels compared with traditional channels.	**Chapter II** Competing Risks for Train Tickets *Research Aim:* Providing empirical evidence of success drivers and performance in CRM practices. *Methodological Approach:* Semi-parametric proportional hazards model stratified by failure type; based on customer loyalty program data. *Results:* Installing auto-renewal procedures decreases cancellation risks, automated electronic mailings and advertising can be counterproductive and increase the risk of cancellation. The findings offer practical implications for transportation companies and other service sectors and provide performance and policy implications for suppliers of comparable transportation services as well as strategic impulses for firms applying two-part pricing schemes in general.	FIRM PERSPECTIVE
	Chapter III Learning Effects in Loyalty Programs *Research Aim:* Providing empirical evidence on the impact of learning effects in loyalty card usage and pricing issues on cancellation behavior over time. *Methodological Approach:* Sequential logit model, t-tests; based on customer loyalty program data. *Results:* The structure of learning curves differs (learn vs. unlearn, low- vs. high-price context); learning effects and pricing strategies do have an impact on retention rates and their influence changes with ongoing contract duration; For structuring customer loyalty programs, the implication for marketing managers is to consider behavior patterns as a result of tariff arrangements and to facilitate learning how to correctly use the loyalty cards, thus leading to associated higher retention rates.	**Chapter IV** The Success of Art Galleries *Research Aim:* Providing empirical evidence of dynamic processes that take effect such that a small, inconsequential firm becomes dominant in a field; including economical interpretation of corresponding model parameters. *Methodological Approach:* Stochastic processes from statistical physics, Kolmogorov-Smirnov tests, Clauset power law test; based on German art market data (*Kunstkompass*) over several years. *Results:* The success of art galleries depends strongly on information and innovation effects, but is hardly affected by competition effects; the superstar effect in the case of art galleries can be understood as an appropriation of search and entrance costs which emerge whenever consumption requires special knowledge and social inclusion.	

Figure 2. *Integrative Framework*

IV. REFERENCES

Acquaah, Moses, and Masoud Yasai-Ardekani (2008). Does the implementation of a combination competitive strategy yield incremental performance benefits? A new perspective from a transition economy in Sub-Saharan Africa. *Journal of Business Research*, 61(4), 346–354.

Adler, Moshe (1985). Stardom and talent. *The American Economic Review*, 75(1), 208–212.

Akerlof, George A. (1970). The market for 'lemons': Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3), 488–500.

Armstrong, Mark (2006). Competition in two-sided markets. *The RAND Journal of Economics*, 37(3), 668–691.

Ascarza, Eva, Anja Lambrecht, and Naufel Vilcassim (2012). When talk is ‘free’: The effect of tariff structure on usage under two- and three-part tariffs. *Journal of Marketing Research*, 49(6), 882–899.

Bagh, Adib, and Hemant K. Bhargava (2007). *Doing more with less: Price discrimination with three-part vs. two-part tariffs*. Davis, CA: University of California.

Barney, Jay (1997). *Gaining and sustaining competitive advantage*. New Jersey: Prentice Hall.

Bauer, Hans H., Mark Grether, and Mark Leach (2002). Building customer relations over the Internet. *Industrial Marketing Management*, 31(2), 155–63.

Baumol, William J. (1986). Unnatural value: Or art investment as a floating crap game. *The American Economic Review*, 76(2), 10–14.

Becker, Howard S. (1982). *Art worlds*. Berkeley, Los Angeles: University of California Press.

Besanko, David, David Dranove, Mark Shanley, and Scott Schaefer (2010). *Economics of strategy*. Hoboken: John Wiley & Sons.

Bolton, Ruth N., Prasanna K. Kannan, and Matthew D. Bramlett (2000). Implications of loyalty program membership and service experiences for customer retention and value. *Journal of the Academy of Marketing Science*, 28(1), 95–108.

Bolton, Lisa E., Luk Warlop, and Joseph W. Alba (2003). Consumer perceptions of price (un)fairness. *Journal of Consumer Research*, 29(4), 474–491.

Boulding, William, Richard Staelin, Michael Ehret, and Wesley J. Johnston (2005). A customer relationship management roadmap: What is known, potential pitfalls, and where to go. *Journal of Marketing*, 69(4), 155–166.

Brown, James R., and Rajiv P. Dant (2009). The theoretical domains of retailing research: A retrospective. *Journal of Retailing*, 85(2), 113–128.

Brynjolfsson, Erik, and Haim Mendelson (1993). Information systems and the organization of modern enterprise. *Journal of Organizational Computing*, 3(3), 245–255.

Caves, Richard E. (2000). *Creative industries: Contracts between art and commerce*. Cambridge: Harvard University Press.

Clifton, Christopher (2013). *Data mining*. Encyclopedia Britannica Online. Retrieved 2013-01-07.

Currid, Elizabeth (2007). *The Warhol economy: How fashion, art and music drive New York City*. Princeton: Princeton University Press.

Darley, William K., and Charles Blankson (2010). Toward an integrated framework for online consumer behavior and decision making process: A review. *Psychology & Marketing*, 27(2), 94–116.

Daugherty, Patricia J., Haozhe Chen, Daniel D. Mattioda, and Scott J. Grawe (2009). Marketing/logistics relation-ships: Influence on capabilities and performance. *Journal of Business Logistics*, 30(1), 1–18.

Day, George S. (2004). Invited commentaries on ‘evolving to a new dominant logic for marketing’: achieving advantage with a new dominant logic. *Journal of Marketing*, 68(1), 18–19.

Della Vigna, Stefano, and Ulrike Malmendier (2006). Paying not to go to the gym. *American Economic Review*, 96(3), 694–719.

Dess, Gregory G., and Peter S. Davis (1984). Porter’s (1980) generic strategies as determinants of strategic group membership and organizational performance. *Academy of Management Journal*, 27(3), 467–488.

De Vries, Erik J. (2006). Innovation in services in networks of organizations and in the distribution of services. *Research Policy*, 35(7), 1037–1051.

Ehrmann, Thomas, Brinja Meiseberg, and Christian Ritz (2009). Superstar effects in deluxe gastronomy – An empirical analysis of value creation in German quality restaurants. *Kyklos*, 62(4), 526–541.

Eisenmann, Thomas, Geoffrey Parker, and Marshall W. van Alstyne (2006). Strategies for two-sided markets. *Harvard Business Review*, 84(10), 1–11.

Ellinger, Alexandeer E., Patricia J. Daugherty, and Craig M. Gustin (1997). The relationship between integrated logistics and customer service. *Transportation Research Part E: Logistics and Transportation Review*, 33(2), 129–138.

Ellinger, Alexandeer E., Patricia J. Daugherty, and Quentin J. Plair (1999). Customer satisfaction and loyalty in supply chain: The role of communication. *Transportation Research Part E: Logistics and Transportation Review*, 35(2), 121–134.

Feldstein, Martin S. (1972). Equity and efficiency in public sector pricing: The optimal two-part tariff. *The Quarterly Journal of Economics*, 86(2), 175–187.

Flavián, Carlos, and Miguel Guinalíu (2005). The influence of virtual communities on distribution strategies in the Internet. *International Journal of Retail & Distribution Management*, 33(6), 405–425.

Franck, Egon, and Stephan Nüesch (2007). Avoiding 'star wars' – Celebrity creation as media strategy. *Kyklos*, 60(2), 211–230.

Galbraith, Jay (1977). *Organization design.* Reading, MA: Addison-Wesley.

Ganesan, Shankar, Morris George, Sandy Jap, Robert W. Palmatier, and Barton Weitz (2009). Supply chain management and retailer performance: emerging trends, issues, and implications for research and practice. *Journal of Retailing*, 85(1), 84–94.

Gijsbrechts, Els (1993). Prices and pricing research in consumer marketing: Some recent developments. *International Journal of Research in Marketing*, 10(2), 115–151.

Goettler, Ronald L., and Karen Clay (2011). Tariff choice with consumer learning and switching costs. *Journal of Marketing Research*, 48(4), 633–652.

Grant, Robert M. (2010). *Contemporary strategy analysis*. Chichester: John Wiley & Sons.

Grawe, Scott J., Patricia J. Daugherty, Rajiv P. Dant (2012). Logistics service providers and their customers: Gaining commitment through organizational implants. *Journal of Business Logistics*, 33(1), 55–63.

Grewal, Dhruv, and Michael Levy (2007). Retailing research: Past, present, and future. *Journal of Retailing*, 83(4), 447–464.

Grewal, Dhruv, and Michael Levy (2009). Emerging issues in retailing research. *Journal of Retailing*, 85(4), 522–526.

Grubb, Michael D. (2009). Selling to overconfident consumers. *American Economic Review*, 99(5), 1770–1807.

Grubb, Michael D., and Matthew Osborne (2012). Cellular service demand: Biased beliefs, learning, and bill shock. *MIT Sloan Research Paper*, No. 4974–12.

Gunasekaran, Angappa, Kee-hung Lai, and T.C. Edwin Cheng (2008). Responsive supply chain: A competitive strategy in a networked economy. *Omega*, 36(4), 549–564.

Gupta, Gaurav, and Himanshu Aggarwal (2012). Improving customer relationship management using data mining. *International Journal of Machine Learning and Computing*, 2(6), 874–877.

Hayek, Friedrich A. (1945). The use of knowledge in society. *American Economic Review,* 35(4), 519–530.

Hayes, Beth (1987). Competition and two-part tariffs. *The Journal of Business*, 60(1), 41–54.

Hitt, Lorin M., and Frances X. Frei (2002). Do better customers utilize electronic distribution channels? The case of PC banking. *Management Science*, 48(6), 732–748.

Hogan, John E., Katherine N. Lemon, and Roland T. Rust (2002). Customer equity management: Charting new directions for the future of marketing. *Journal of Service Research*, 5(1), 4–12.

Homburg, Christian, Wayne D. Hoyer, and Martin Fassnacht (2002). Service orientation of a retailer's business strategy: Dimensions, antecedents, and performance outcomes. *Journal of Marketing*, 66(4), 86–101.

Iyengar, Raghuram, Asiim Ansari, and Sunil Gupta (2007). A model of consumer learning for service quality and usage. *Journal of Marketing Research*, 44(4), 529–544.

Jamal, Zainab, and Randolph E. Bucklin (2006). Improving the diagnosis and prediction of customer churn: A heterogeneous hazard modeling approach. *Journal of Interactive Marketing*, 20(3–4), 16–29.

Jensen, Michael C., and William H. Meckling (1992). Specific and general knowledge, and organizational structure, in: Lars Werin and Hans Wijkander (eds.), *Contract economics*. Oxford: Blackwell, 251–274.

Jensen, Sissel (2006). Implementation of competitive nonlinear pricing: Tariffs with inclusive consumption. *Review of Economic Design*, 10(1), 9–29.

Kahneman, Daniel, and Amos Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 163–191.

Kim, Byung-Do, Mengze Shi, and Kannan Srinivasan (2001). Reward programs and tacit collusion. *Marketing Science*, 20(2), 99–120.

Kim, Donghoon, Seung-yon Lee, Kyunghee Bu, and Seho Lee (2009). Do VIP programs always work well? The moderating role of loyalty. *Psychology & Marketing*, 26(7), 590–609.

Kotha, Suresh, and Bhatt L. Vadlamani (1995). Assessing generic strategies: An empirical investigation of two competing typologies in discrete manufacturing industries. *Strategic Management Journal*, 16(1), 75–83.

Kumar, V., and Denish Shah (2004). Building and sustaining profitable customer loyalty for the 21st century. *Journal of Retailing*, 80(4), 317–329.

Lambrecht, Anja, and Bernd Skiera (2006). Paying too much and being happy about it: Existence, causes and consequences of tariff-choice biases. *Journal of Marketing Research*, 43(2), 212–23.

Kutner, Steve, and John Cripps (1997). Managing the customer portfolio of healthcare enterprise. *The Healthcare Forum Journal*, 40(5), 52–54.

Leenheer, Jorna, Harald J. van Heerde, Tammo H. A. Bijmolt, and Ale Smidts (2007). Do loyalty programs really enhance behavioral loyalty? An empirical analysis accounting for self-selecting members. *International Journal of Research in Marketing*, 24(1), 31–47.

Levary, Reuven R., and Richard G. Mathieu (2000). Hybrid retail: Integrating e-commerce and physical stores. *Industrial Management*, 42(5), 6–11.

Lewis, Michael V. (2004). The influence of loyalty programs and short-term promotions on customer retention. *Journal of Marketing Research*, 41(3), 281–292.

Li, Zhi-Chun, William H. K. Lam, S.C. Wong, and A. Sumalee (2012). Design of a rail transit line for profit maximization in a linear transportation corridor. *Transportation Research Part E: Logistics and Transportation Review*, 48(1), 50–70.

MacKie-Mason, Jeffrey K., and Hal R. Varian (1995). Pricing congestible network resources. *IEEE Journal on Selected Areas in Communications*, 13(7), 1141–1149.

McCall, Michael, and Clay Vorhees (2010). The drivers of loyalty program success: An organizing framework and research agenda. *Cornell Hospitality Quarterly*, 51(1), 35–52.

Mägi, Anne W. (2003). Share of wallet in retailing: The effects of customer satisfaction, loyalty cards and shopper characteristics. *Journal of Retailing*, 79(2), 97–106.

Miles, Raymond E., Charles C. Snow, Alan D. Meyer, and Henry J. Coleman, Jr. (1978). Organizational strategy, structure, and process. *The Academy of Management Review*, 3(3), 546–562.

Miller, Alex, and Gregory G. Dess (1993). Assessing Porter’s (1980) model in terms of generalizability, accuracy, and simplicity. *Journal of Management Studies*, 30(4), 553–585.

Miller, Danny, and Peter H. Friesen (1986a). Porter's (1980) generic strategies and performance: An empirical examination. Part I: Testing Porter. *Organization Studies*, 7(1), 37–55.

Miller, Danny, and Peter H. Friesen (1986b). Porter's (1980) generic strategies and performance: An empirical examination. Part II: Performance implications. *Organization Studies*, 7(3), 255–261.

Mimouni-Chaabane, Aîda, and Pierre Volle (2010). Perceived benefits of loyalty programs: Scale development and implications for relational strategies. *Journal of Business Research*, 63(1), 32–37.

Mintzberg, Henry, and James B. Quinn (1988). *The strategy process: Concepts, contexts, cases*. New Jersey: Prentice Hall.

Mithas, Sunil, Mayuram S. Krishnan, and Claes Fornell (2005). Why do customer relationship management applications affect customer satisfaction? *Journal of Marketing*, 69(4), 201–209.

Murphy, Michael M. (1977). Price discrimination, market separation, and the multi-part tariff. *Economic Inquiry*, 15(4), 587–599.

Oi, Walter Y. (1971). A Disneyland Dilemma. Two-part tariffs for a Mickey Mouse monopoly. *The Quarterly Journal of Economics*, 85(1), 77–96.

Park, Do-Hyung, Jumin Lee, and Ingoo Han (2007). The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. *International Journal of Electronic Commerce*, 11(4), 125–148.

Pavlou, Paul A., and Mendel Fygenson (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly*, 30(1), 115–143.

Payne, Adrian, and Pennie Frow (2005). A strategic framework for customer relationship management. *Journal of Marketing*, 69(4), 167–176.

Phillips, Lynn W., Dae R. Chang, and Robert D. Buzzell (1983). Product quality, cost position and business performance: A test of some key hypotheses. *Journal of Marketing*, 47(2), 26–43.

Podolny, Joel M. (1994). Market uncertainty and the social character of economic change. *Administrative Science Quarterly*, 39(3), 458–483.

Porter, Michael E. (1980). *Competitive strategy*. New York: Free Press.

Porter, Michael E. (1985). *Competitive advantage*. New York: Free Press.

Ramanathan, Ramakrishnan (2010). The moderating roles of risk and efficiency on the relationship between logistics performance and customer loyalty in e-commerce. *Transportation Research Part E: Logistics and Transportation Review*, 46(6), 950–962.

Reimann, Martin, Oliver Schilke, and Jacquelin S. Thomas (2010). Customer relationship management and firm performance: The mediating role of business strategy. *Journal of the Academy of Marketing Science*, 38(3), 326–346.

Ritchie, Robert O., and Clare S. Brindley (2007). An emergent framework for supply chain risk management and performance measurement. *Journal of the Operational Research Society*, 58(11), 1398–1411.

Rochet, Jean-Charles, and Jean Tirole (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, 1(4), 990–1029.

Rochet, Jean-Charles, and Jean Tirole (2006). Two-sided markets: a progress report. *The RAND Journal of Economics*, 37(3), 645–667.

Rosen, Sherwin (1981). The economics of superstars. *American Economic Review*, 71(5), 845–858.

Rysman, Marc (2009). The economics of two-sided markets. *Journal of Economic Perspectives*, 23(3), 125–143.

Schmale, Hendrik, Thomas Ehrmann, and Alexander Dilger (2013). Buying without using – Biases of German BahnCard buyers. *Applied Economics*, 45(7), 933–941.

Shugan, Steven M. (2005). Brand loyalty programs: Are they shams. *Marketing Science*, 24(2), 185–193.

Smith, Andrew S. J. (2012). The application of stochastic frontier panel models in economic regulation: Experience from the European rail sector. *Transportation Research Part E: Logistics and Transportation Review*, 48(2), 503–515.

Srinivasan, Srini S., Rolph Anderson, and Kishore Ponnavolu (2002). Customer loyalty in e-commerce: An exploration of its antecedents and consequences. *Journal of Retailing*, 78(1), 41–50.

Steven, Adams B., Yan Dong, and Martin Dresner (2012). Linkages between customer service, customer satisfaction and performance in the airline industry: Investigation of non-linearities and moderating effects. *Transportation Research Part E: Logistics and Transportation Review*, 48(4), 743–754.

Teece, David J., Gary Pisano, and Amy Shuen (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533.

Thaler, Richard H. (1985). Mental accounting and consumer choice. *Marketing Science*, 4(3), 199–214.

Thaler, Richard H., and Eric J. Johnson (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, 36(6), 643–660.

Tirole, Jean (1988). *The theory of industrial organization*. Cambridge: The MIT Press.

Tsai, Dungchun, and Hsiao-Ching Lee (2009). Demographics, psychographics, price searching and recall in retail shopping. *The Service Industries Journal*, 29(9), 1243–1259.

Wallace, David W., Joan L. Giese, and Jean L. Johnson (2004). Customer retailer loyalty in the context of multiple channel strategies. *Journal of Retailing*, 80(4), 249–263.

Webb, Kevin L. (2002). Managing channels of distribution in the age of electronic commerce. *Industrial Marketing Management*, 31(2), 95–102.

Wen, Chieh-Hua, Wei-Chung Wang, and Chiang Fu (2012). Latent class nested logit model for analyzing high-speed rail access mode choice. *Transportation Research Part E: Logistics and Transportation Review*, 48(4), 545–554.

Williamson, Oliver E. (1975). *Markets and Hierarchies: Analysis and Antitrust Implications*. New York: Free Press.

Winer, Russell S. (2001). A framework for customer relationship management. *California Management Review*, 43(4), 89–105.

Xia, Lan, Kent B. Monroe, and Jennifer L. Cox (2004). The price is unfair! A conceptual framework of price fairness perceptions. *Journal of Marketing*, 68(4), 1–15.

Yao, Dong-Qing, and John J. Liu (2005). Competitive pricing of mixed retail and e-tail distribution channels. *Omega*, 33(3), 235–247.

Yin, Xiangkang (2004). Two-part tariff competition in duopoly. *International Journal of Industrial Organization*, 22(6), 799–820.

Zhang, Z. John, Aradhna Krishna, and Sanjay K. Dhar (2000). The optimal choice of promotional vehicles: Front-loaded or rear-loaded incentives. *Management Science*, 46(3), 348–362.

Zablah, Alex R., Danny N. Bellenger, and Wesley J. Johnston (2004). An evaluation of divergent perspectives on customer relationship management: Towards a common understanding of an emerging phenomenon. *Industrial Marketing Management*, 33(6), 475–489.

PART B

I. DO ONLINE CUSTOMERS MAKE BETTER PURCHASES? – AN ANALYSIS OF POINT OF SALE CHOICE AND ITS LINKAGES TO CUSTOMER LOYALTY AND THE (IR)RATIONALITY OF BUYING DECISIONS

"The real voyage of discovery consists not in seeking new lands, but seeing with new eyes."
Marcel Proust (1871-1922)

1. Abstract

Based on a large-scale, unique longitudinal dataset comprising more than four million individual transactions, we study linkages between points of sale and consumers' purchase behavior. We focus on online versus traditional over-the-counter channels. First, we investigate consumer-inherent and contingent factors that drive customers' point of sale choice. Second, adopting a consumer perspective, we study whether online purchases or counter purchases tend to yield higher purchase decision quality. We establish whether such linkages hold across different customer segments and pricing contexts, and we also examine consumers' learning effects in terms of improving on decision quality over time. Third, moving on to the firm perspective, we study subsequent customer loyalty in either distribution channel, and explore how loyalty develops across different segments, pricing contexts, and levels of decision quality. Hypotheses are tested in the context of two-part pricing schemes in travel services that are particularly intended to create customer loyalty, and offer a rare opportunity for an objective assessment of purchase optimality. Our results show how various consumer-inherent and contingent factors affect point of sale choice. Contrary to our expectations, the rationality of purchase decisions is in fact dependent on the chosen point of sale. Besides, it largely varies across customer segments. However, learning effects do occur over time, yet their strength differs across low- and high-price

contexts as well as across consumer groups. Loyalty depends on both pricing contexts and segments as well as on customers' previous decision quality and point of sale choice. We provide implications for upgrading consumers' purchase behavior and for segment-specific customer acquisition and retention.

2. Introduction

More and more firms pursue electronic distribution strategies to augment their physical infrastructure for product and service delivery (Hitt and Frei 2002; Laroche et al. 2005; Pan and Zhang 2011). As the Internet has evolved into an important distribution channel and marketing medium, it has profoundly transformed the way consumers shop and gather information (Bart et al. 2005; Grewal and Levy 2009). At the same time, competitive retail environments and decreasing switching costs make customers ever more difficult to retain (Srinivasan, Anderson, and Ponnavolu 2002). Under these challenging conditions, retailers must allocate their resources effectively within and across distribution channels to create sustainable customer relationships (Bart et al. 2005).

As investments in customer relationships and multichannel distribution become increasingly central to long-term company strategies, an essential question is how using different distribution channels adds value to firms that invest in them (Hitt and Frei 2002). Yet, there is a lack of research into customer characteristics that drive the use of online purchase systems versus traditional channels (Brown and Dant 2009; Hitt and Frei 2002; Reinartz, Krafft, and Hoyer 2004; Wallace, Giese, and Johnson 2004), and the question of how different channels affect consumer behavior and customer loyalty remains surprisingly unanswered to date (Brown and Dant 2009; Hitt and Frei 2002; Homburg, Hoyer, and Fassnacht 2002; Reinartz, Krafft, and Hoyer 2004; Wallace, Giese, and Johnson 2004).

Across distribution channels, customer loyalty is a critical goal for firms (Jacoby and Chestnut 1978; Laroche et al. 2005; Wallace, Giese, and Johnson 2004). Loyal customers buy more often, are willing to pay higher prices, and generate positive word of mouth (Oliver 1997; Reichheld 1993; Wallace, Giese, and Johnson 2004; Zeithaml, Berry, and Parasuraman 1996). Accordingly, many companies initiate loyalty programs, particularly in the service sector. Loyalty programs provide consumers with incentives for repeat business, which encourages them to continue their purchase behavior (Keh and Lee 2006). Bolton, Kannan, and Bramlett (2000), Keh and Lee (2006), Leenheer (2007), Meyer-Waarden (2008), or Vesel and Zabkar (2009) study outcomes of such programs, particularly, behavioral loyalty and retention. Yet, Berman (2006) and Keh and Lee (2006) argue that despite their proliferation, many programs do not produce the results desired by the firm. Still, insights into the responsiveness across different customer segments and their respective buying behavior as well as effects of loyalty programs in different channels are unfortunately scarce (Allaway et al. 2006; Gommans, Krishnan, and Scheffold 2001; Ramsay 2010; Shankar, Smith, and Rangaswamy 2003). In sum, research has not adequately considered market-level responses to retailing strategies in online vs. offline distribution, although this is of essential importance to researchers as well as practitioners (Peterson and Balasubramanian 2002).

Based on an extensive, proprietary, longitudinal dataset comprising more than four million individual consumer transactions, we provide insights into this context by studying linkages between consumers' point of sale choice and purchase behavior. First, we investigate how consumer-inherent and contingent factors drive point of sale (PoS) preferences in terms of choosing online versus traditional over-the-counter channels. Second, from a consumer perspective, we study whether Internet purchases or counter purchases tend to yield higher purchase decision quality, and whether these linkages hold across different segments and pricing contexts. We also explore learning effects concerning potential improvements on the quality of consumers' purchase decisions over time. Third, moving on to the firm perspective, we study subsequent loyalty behavior of customers choosing either distribution channel, and examine how such loyalty relates to different customer segments, pricing contexts and levels of previous decision quality.

Hypotheses are tested in the context of two-part pricing schemes (loyalty cards) in services, as these are particularly intended to create customer loyalty, and offer a rare opportunity for an objective assessment of purchase optimality. We focus on the German rail travel sector, where consumers can choose to buy loyalty cards that allow them certain discounts on future fares. Thus, the analysis is based on one of the most prominent loyalty programs in the largest European economy (*BahnCard*, 4.5 million participants in 2011). Our results document how a range of consumer-inherent and contingent factors affect PoS choice. We can also establish that contrary to our expectations, the quality, or rationality, of purchase decisions in fact depends on the chosen PoS. Besides, it largely varies across customer groups and high- vs. low-price contexts. Moreover, learning effects do occur over time, yet their strength varies across consumer segments as well as pricing contexts and chosen PoS. Customer loyalty depends on all these aspects: on PoS choice, the rationality of previous purchase decisions, as well as customer segments and pricing contexts. We contribute to the retailing literature by offering theoretical and managerial implications.

The paper is organized as follows: In the next chapter, we explain the conceptual background to the study. The third section presents hypotheses. Subsequently, we describe our data and methods. Section 5 summarizes our results. The last section concludes and offers implications.

3. Conceptual Background

Point of Sale. Firms have increasingly transitioned to hybrid models that integrate physical stores and online systems – for example, retailers like Barnes and Noble or Wal-Mart have combined outlet stores with substantial investments in an attractive online presence (Hitt and Frei 2002). Particularly in services, firms frequently mix online and counter distribution to augment or even supplant 'traditional' distribution (e.g., travel agents, financial institutions, insurance providers).

There is little systematic knowledge about the drivers that make consumers prefer Internet versus traditional channels (Gommans, Krishnan, and Scheffold 2001; Ramsay 2010; Shankar, Smith, and Rangaswamy 2003). Previous research in consumer behavior applies risk theory and suggests that consumers make purchase decisions according to the perceived risk inherent in the decision (Hitt and Frei 2002; Laroche et al. 2005; Weathers, Sharma, and Wood 2007). Perceived risk exhibits two components – uncertainty (the likelihood of unfavorable outcomes) and consequences (the importance of a potential loss) (Bauer 1960; Cox and Rich 1964; Mitchell and Greatorex 1993). The assessment of buying options on the consumer side depends on the consumer's confidence in the ability to make the 'right' purchase decision, which is also contingent on the *place of purchase* (Mitchell and Greatorex 1993). Due to the 'intangibility' inherent in online purchases, online channels are commonly believed to increase perceived risk and assessment difficulties compared with traditional over-the-counter settings. However, Berthon et al. (1999), Laroche et al. (2005), and Thakor, Borsuk, and Kalamas (2004) also discuss the functionality of the Internet in offering a plethora of information to consumers who are willing to search for it, suggesting that the Internet should facilitate purchase decisions rather than complicate them.

Accordingly, demographic characteristics – to the extent that they are linked to what consumers perceive as desirable skills to acquire and behaviors to adopt – can induce preferences for either distribution channel (Hitt and Frei 2002). Several market research studies (e.g., Zickuhr and Smith 2012) show that the average PC user, who may engage in online purchasing, is younger and more affluent than the average population. Consumers using online banking have also been found to differ from counter users in demographic characteristics (Hitt and Frey 2002). Besides, aspects like risk aversion, experience in acquiring information online, or preferences for engaging in interaction with salespersons versus online exchange, may drive consumers to choose Internet or counter PoS (Barber and Odean 1999; Hitt and Frey 2002; Oestreicher-Singer and Sundararajan 2010). Resulting from these diverging characteristics and preferences, consumers' subsequent decision-making processes and purchase behavior might differ as well.

(Ir)Rationality of Purchase Behavior. Brown and Dant (2009) note that researchers who investigate topics involving the Internet should utilize theories not frequently applied, like microeconomic theory, consumer choice theory, and social exchange theory. Consequently, our analysis is based on the microeconomic model of expected utility maximization, which implies that individuals choose an object over another if this object is assigned a higher value by the consumer's specific preference function (Hirshleifer 1965; Machina 2008; Von Neumann and Morgenstern 1944). We assume that consumers try to achieve the highest level of utility possible in their choice of a particular offering. Yet obviously, they face constraints in satisfying their wishes as extended search for 'adequate' purchases becomes complicated and time-consuming. Consumers' rationality in forming preferences is limited by the information they can acquire, by cognitive limitations, and by the finite amount of time available to reach a decision (Baumol and Quandt 1964; Rubinstein 1998; Simon 1957). Given the context at hand, the optimality of purchase decisions is comparatively easy to assess (*for consumers as well*) by a simple cost-benefit approach. There are three possible scenarios, depending on individual travel behavior: First, consumers can 'overuse' their loyalty card, meaning they would be better off overall if they had bought a more expensive card up-front (a more expensive card allows greater reductions on subsequent fares). Second, they may 'underuse' their card, meaning they would benefit more from holding a less expensive card, as the ticket fare reductions gained do not cover the higher initial price paid for the card. Third, consumers may succeed in buying in an 'optimal' way, that is, they would be worse off if they had bought either a cheaper (or none) or a more expensive card. The latter behavior is considered as making a 'rational' or 'optimal' purchase decision in

the following, other behaviors are considered as ‘non-optimal’ or ‘irrational’ (‘beyond optimal’ for over-usage, ‘suboptimal” for under-usage).[6] We suggest that consumers’ decision quality will depend on a range of influential factors, and accordingly, study drivers of consumer choice.

Customer Loyalty. Loyalty has been extensively studied in the literature based on various definitions (Day 1969; Jacoby and Chestnut 1978; Keh and Lee 2006; Oliver 1997). In line with Srinivasan, Anderson, and Ponnalovu (2002), we define ‘loyalty’ as a customer’s favorable attitude towards the firm that *results in repeat buying behavior*, placing the focus on actually observable repeat purchasing.[7] Customer loyalty is of extreme interest to firms as it can be strongly linked to profitability (Oliver 1997; Reichheld 1993; Zeithaml, Berry, and Parasuraman 1996), and even a small decrease in customer loyalty can make a large difference for earnings (Wallace, Giese, and Johnson 2004). Loyalty becomes ever more important as the Internet fuels retailing competition and reduces switching costs (Srinivasan, Anderson, and Ponnalovu 2002). Thus, enhancing loyalty is a critical defensive strategy for firms to retain their customer base and prevent customers from switching to competing services. Accordingly, many companies have started loyalty programs to incentivize repeat business and to encourage consumers to continue their transactions with the firm (Keh and Lee 2006). The value and the efficiency of such programs have been the subject of controversial discussions among researchers and practitioners: Despite their proliferation, they often do not produce the results desired by the firm (Bolton, Kannan, and Bramlett 2000; Key and Lee 2006; Leenheer 2007; Meyer-Waarden 2008; Vesel and Zabkar 2009), and little is known about the responsiveness across different customer

---

[6] One may argue that ‘optimality’ is simple to judge in retrospective, yet not when making the buying decision, due to unforeseen changes in circumstances, incorrect but initially plausible assumptions about the future, asf. Then, when considering the circumstances surrounding the specific moment of ex ante decision-making, consumer behavior could still have been rational. However, in light of the very elementary cost-benefit calculation applicable and the fact that numerous sample consumers frequently repeat their initial purchase ‘mistakes’ over years in a row without changing their purchase behavior ever, we suggest that such behavior is often not based on rational decision-making.

[7] Scholars have argued that behavioral loyalty (i.e. repeat purchase) does not capture the multidimensionality of the loyalty construct, as loyalty should also include psychological aspects like commitment (Kumar and Shah 2004). Thus, habitual or convenience purchases, and those induced foremost by promotional incentives, have been cited to explain why “loyalty” programs may appear not to work (Keh and Lee 2006; Kumar and Shah 2004; Uncles, Dowling, and Hammond 2003). Due to data limitations, we follow the more basic approach and focus on repeat purchase, as there is no data on consumers’ psychological drivers and underlying motivations for this extensive dataset.

segments and their respective buying behavior (Allaway et al. 2006; Berman 2006; Keh and Lee 2006).

Against this background, our research questions are:

(1) *Descriptive Perspective:* What consumer-inherent characteristics or contingent factors drive customers' PoS choice when deciding to buy through online versus over-the-counter channels?

(2) *Consumer Perspective:* Does either type of distribution channel tend to yield 'better' results in terms of consumers' purchase decision quality? Do potential linkages apply across customer segments and pricing contexts alike? Can consumers realize learning effects that enhance their decision quality over time, and if so, what conditions accelerate or hamper those learning effects?

(3) *Firm Perspective:* How loyal (in terms of continued purchase behavior) are customers who choose online channels compared with those preferring counter purchase? How are different customer segments, pricing contexts and levels of decision quality related to customer loyalty?

We provide several contributions: First, few studies have explicitly focused on how customer heterogeneity is related to online versus offline purchasing (Hitt and Frei 2002; Tsai and Lee 2009). Although some research has discussed customer characteristics, these are typically not hypothesized to vary between distribution channels (Bakos 1991, 1997; Brynjolfsson and Smith 1998; Clemons, Hann, and Hitt 1999; Hitt and Frei 2002; Lee 1998; Varian and Shapiro 1998). Besides, previous studies on firm prospects in online retailing have emphasized cost savings (e.g., substituting staff costs with lower information technology costs, or transaction cost reductions; Clemons and Row 1992; Gurbaxani and Whang 1991; Malone, Yates, and Benjamin 1987) and revenue increases through price and product differentiation and social network effects (Bailey and Bakos 1997; Clemons, Hann, and Hitt 1999; Oestreicher-Singer and Sundararajan 2010; Varian and Shapiro 1998), but have not focused on determinants of consumer responsiveness to particular channels. We show how customer heterogeneity is related to online versus offline PoS choice and subsequent purchase behavior. Second, although customer satisfaction with purchase decisions is extensively studied, decision quality is not, although it complements satisfaction research by providing a more objective and less volatile assessment of purchase advantageousness. We establish under what conditions customers tend to make better buying decisions and offer some insights into the potential scope and the benefits of learning effects. Third, as retail managers and academics become increasingly interested in issues related to the ‘true’ value of loyalty programs, our results inform e-commerce strategy by offering implications for more effective customer acquisition and retention in the two most important channels. In addition, there is a lack of research into two-part pricing systems across distribution channels, although such pricing schemes are increasingly used and are particularly intended to create customer loyalty. In sum, we add to the literature investigating multichannel distribution, as a better understanding of the linkages between customer heterogeneity, decision quality and loyalty behavior is important for retailers that combine distribution channels, and for allocating resources effectively across and within channels. Our research framework is summarized by Figure 3. The next section presents hypotheses.

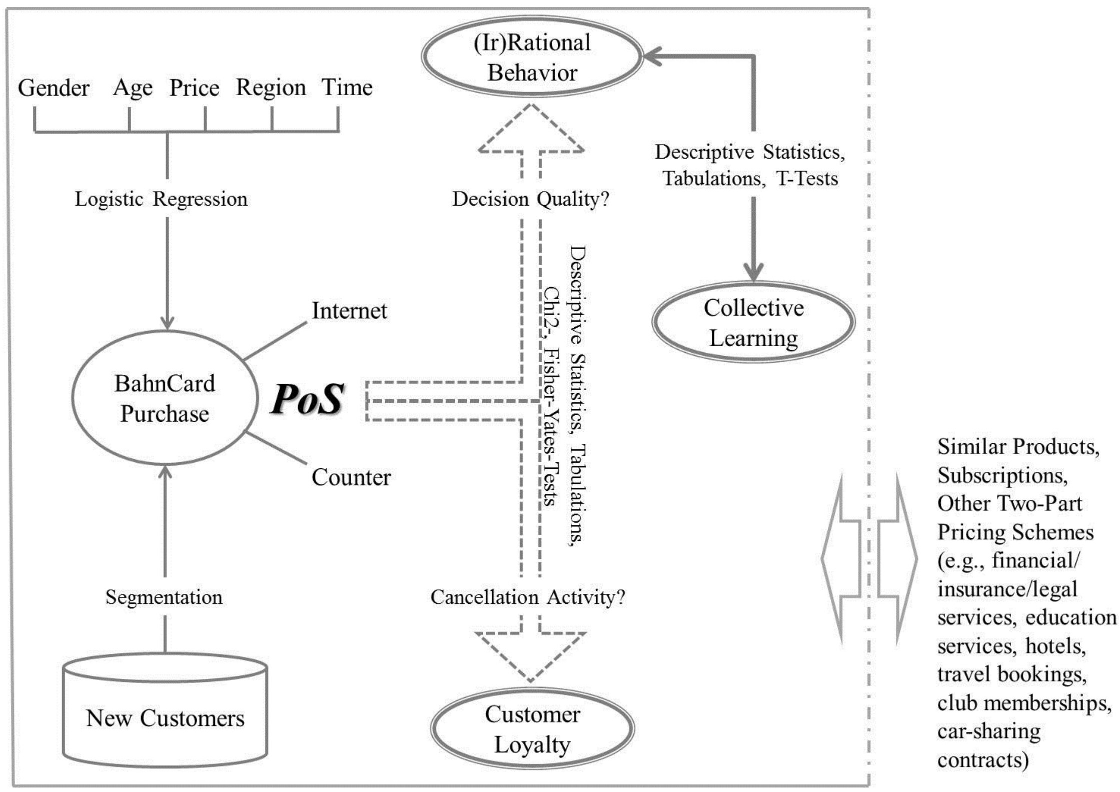


Figure 3. *Research Approach*

4. Hypotheses

4.1 Descriptive Perspective: Point of Sale Choice

Internet usage has been found to vary systematically with consumer characteristics, particularly with demographics (Bart et al. 2005; Mittal and Kamakura 2001; Zickuhr and Smith 2012). For example, consumers lacking Internet experience are more frequent among older than younger age groups. Besides, older consumers tend to perceive online purchasing as more risky, more time-consuming and more difficult than buying via traditional channels (Yoon 2002). Then, the uncertainty involved in any purchase evaluation online may be amplified by feelings of insecurity towards the technology needed to enable the transaction as well as by privacy and security concerns (Hitt and Frei 2002; Laroche et al. 2005; Miyazaki and Fernandez 2001; Weathers, Sharma, and Wood 2007). Previous research also suggests that older people have more persistent shopping habits and value the benefits of an existing transaction pattern more than the young, leading to greater inertia, also as such behavior allows reducing physical and mental efforts (Baltas, Argouslidis, and Skarmeas 2010). Moreover, age is likely to be negatively correlated with other kinds of exploratory behavior as well, like variety seeking and search activity (Guo 2001; Van Kenhove, de Wulf, and Van den Poel 2003).

Scholars have also observed gender differences in shopping behavior concerning information search, the use of price reductions, and responses to store stimuli (Grewal, Gotlieb, and Marmorstein 2003; Harmon 2003; Noble, Griffith, and Adjei 2006; Otnes and McGrath 2001). For example, some studies argue that female customers are more risk-adverse than male ones when making purchase decisions, whereas male customers have been found to be more benefit-oriented, show a greater willingness to gather information, and display greater confidence in processing information as well a more achievement-oriented purchase behavior (Baltas, Argouslidis, and Skarmeas 2010; Noble, Griffith, and Adjei 2006; Otnes and McGrath 2001).

In addition, various contingent factors may influence PoS preferences. For example, geographical regions vary in population density. Densely populated regions may offer more counter purchase options (and concerning the study context, a higher number of travel destinations and more frequent schedules, rendering the possession of a loyalty card more attractive compared with regions where rail travel is less convenient). Also, they may offer better infrastructure in general, including faster Internet connections or more choices among providers, or its population may be more affluent and experienced with Internet purchases than the population in less developed areas. Consequently, the regional setting could affect consumer choices.

Moreover, the price of a good or service determines how critical the risk of 'buying something wrong' is perceived. Therefore, the price level should be a central criterion for consumers' motivation to reduce purchase uncertainty, which may also drive channel choice (Grewal, Gotlieb, and Marmorstein 1994; Shimp and Bearden 1982a, 1982b). Besides, depending on consumer characteristics, some consumers may refrain from online purchases in high-price settings, whereas others may even prefer acquiring information online and deliberately use the Internet in case of high-price purchases. Then, the pricing context may also moderate effects of consumer-inherent characteristics as well as contingent factors on PoS choice, for example, as some customer segments and regional subcultures may be more risk averse or face stronger budget constraints than others. Accordingly, we hypothesize:

H1: Consumer-inherent as well as contingent factors determine customers' point of sale choice.

H1a: Customers' point of sale choice varies with age.

H1b: Customers' point of sale choice varies across genders.

H1c: Customers' point of sale choice varies across geographical regions.

H1d: Customers' point of sale choice varies across high- and low-price contexts.

H1e: The effect of pricing contexts on customers' point of sale choice varies with age, gender, and across geographical regions.

4.2 Consumer Perspective

Consumers must allocate their budgets in a way that best serves their individual needs, given constraints of time and information processing abilities. As consumers *themselves* choose to buy online versus offline according to where they believe to find the information needed for taking informed decisions, systematic differences between online and counter purchases as regards the level of decision quality are not necessarily to be expected. Rather, consumers self-select into their respectively preferred channel which they perceive as the 'better' transaction means.

However, decision quality will depend on consumers' motivation to invest efforts into the purchase decision. Then, decision quality may vary across low- and high-price settings, as customers may pay more attention if "more money is at risk" (Dowling and Staelin 1994; Ross 1975). Moreover, some customer segments may make more well-considered decisions as they are more risk-averse or face more budget constraints than others. Life experience may also promote individuals' decision quality, so that decision quality likely varies across customer segments.

Zeithaml, Berry, and Parasuraman (1993) find that similar to experience, prior knowledge of a product or service allows for a clearer mental representation of it. Such representation helps diminish the risk associated with a purchase, and by causing greater ease of evaluation, it lowers the efforts needed for making a good decision (Laroche et al. 2005). Accordingly, decision quality should increase with repeated buying. Besides, customers may also inform others interested in the respective offering. Particularly in high-price contexts, consumers may pay more attention to the quality of their purchase decisions, and strive for learning from purchasing mistakes for future decisions. Some customer segments may be more inclined to learn, e.g., due to greater risk-aversion or higher achievement orientation. However, if PoS choices are not systematically related to decision quality, learning capacities of customers may not depend on channel choice, either.

This is formulated in the following hypotheses:

H2: The quality of consumers' purchase decisions does not depend on online versus offline point of sale choice.

H2a: Purchase decision quality varies across low- and high-price contexts.

H2b: Purchase decision quality varies across customer segments.

H2c: Purchase decision quality increases over time.

H2d: The increase in purchase decision quality varies across low- and high-price contexts and across customer segments, but not across points of sale.

4.3 Firm Perspective

Although studies on loyalty programs in the traditional counter environment are plentiful, little empirical research is available for online sales situations, particularly, based on large-scale data (Gommans, Krishnan, and Scheffold 2001; Ramsay 2010; Shankar, Smith, and Rangaswamy 2003). Some evidence indicates that online customers are likely less loyal than counter customers, as electronic means of communication do not foster commitment as much as personal interaction (De Berranger and Meldrum 2000; Granovetter 1973; Uzzi 1999). Personal contact and face-to-face encounters with salespeople may then create a greater sense of familiarity with the service or the company for consumers (Gulati 1995; Uzzi 1999). Besides, online customers may be more variety-seeking in general, as low search costs in online channels allow them to consider a greater range of purchase options (Anderson 2006; Elberse 2008). In consequence, online customers may tend to try out competing services or switch to other product and service categories more frequently (Baumgartner and Steenkamp 1996; Kahn 1995; McAlister and Pessemier 1982; Ramsay 2010; Ratner, Kahn, and Kahneman 1999; Tang and Chin 2007). On the contrary, some scholars claim that customers could even be more loyal online (Shankar, Smith, and Rangaswamy 2003), whereas other expect little differences overall (Walsh et al. 2010).

Moreover, although loyalty has been studied extensively in the literature, its relation to retail pricing strategies is not well understood (Allender and Richards 2012). Yet, pricing contexts should affect loyalty behavior as in high-price contexts more pronounced risk aversion may rather drive consumers to stick with a firm whose services have proven satisfactory. In addition, preferences for repeat purchase behavior may vary by customer segments, e.g. depend on the respective tendencies towards inertia or variety-seeking behavior. Similarly, customers who have made adequate purchase decisions in the past benefit more from staying with their particular firm compared with others who display non-optimal decision quality. The latter consumers may also blame their 'bad' decisions, once noticed, on the firm rather than on their own behavior, possibly resulting in reduced motivation to stay loyal to the company.

Formally:

H3: Customer loyalty depends on online versus offline point of sale choice.

H3a: Customer loyalty varies across low- and high-price contexts.

H3b: Customer loyalty varies across customer segments.

H3c: Customer loyalty varies with purchase decision quality.

Figure 4 summarizes our hypotheses framework.

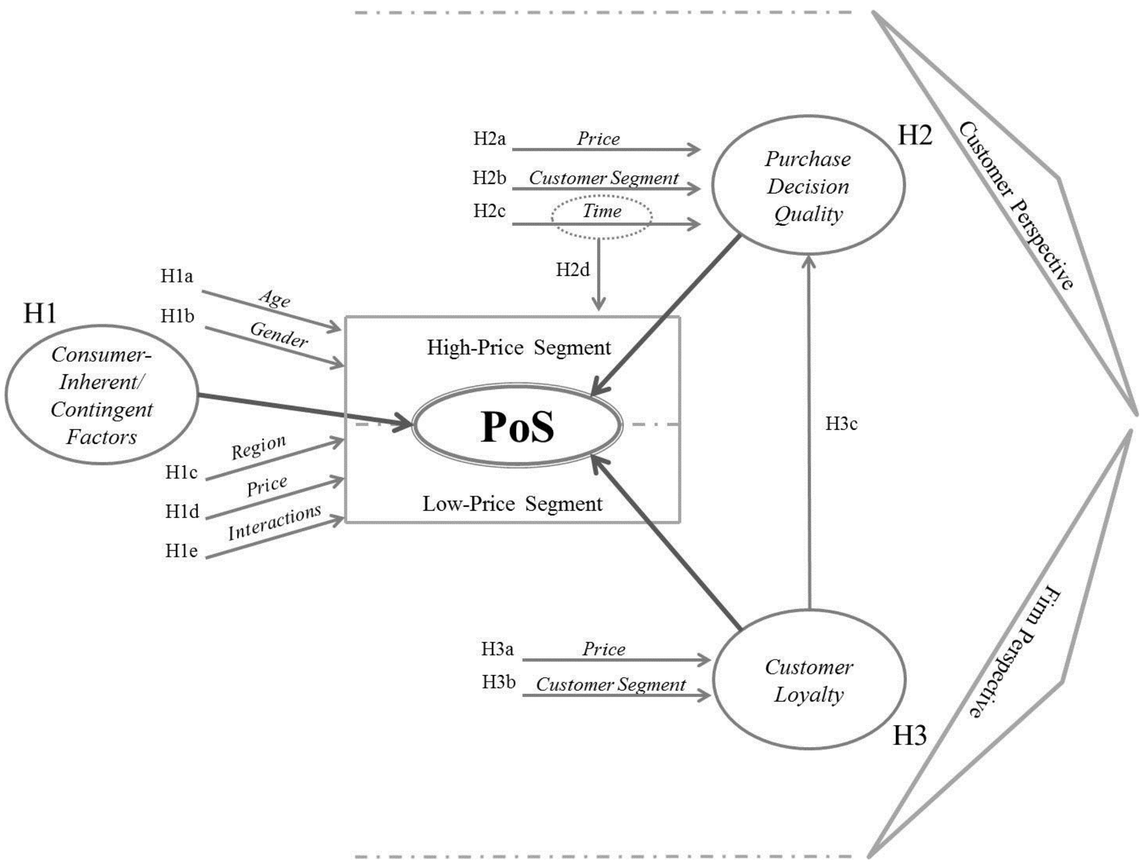


Figure 4. *Hypotheses Framework*

5. Data, Variables and Methods

5.1 Sample

The data were provided by the main German railway company *Deutsche Bahn AG* (DB) and drawn from the customers in DB's customer loyalty programs 'bahn.bonus' and 'bahn.comfort'. They include more than four million transactions conducted with any of the 800,000 BahnCards in the sample, encompassing the entire purchase history of over 300,000 customers. DB customers can basically choose between three contracts: the BahnCard25 (BC25), the BahnCard50 (BC50) and the BahnCard100 (BC100). Each contract is available for first and second class travel. The number of the BahnCard contract type signifies the discount it affords on the regular ticket price for a 12 month period from the date of issue. Thus a BC25 gives a 25% discount, a BC50 means a 50% discount and a BC100 means a 100% reduction on standard domestic fares for a year. Currently, standard second class BahnCard contracts cost EUR 57 for the BC25, EUR 230 for the BC50 and EUR 3,800 for the BC100. First class variants cost EUR 114 for the BC25, EUR 460 for the BC50 and EUR 6,400 for the BC100.

Some adjustments were made to enhance reliability of the database. First, we excluded all program members whose overall lifetime sales did not exceed zero. Then, we dropped customers with inconsistent or not clearly assignable contracts (resulting from e.g., goodwill cancellations or registration errors). We concentrate on second class BahnCards only to ensure contracts are comparable. For analyzing PoS choice, decision quality, and loyalty, we focus on customers that newly join the loyalty program, i.e. BC25 and BC50 customers (as BC100 users do not purchase any tickets due to their flat rate travel advantage, their decision quality cannot be monitored) that bought their first BahnCard during the sample period from December 2002 through July 2008. For investigating learning effects, we focus on the entire sample's purchase history. The winter of 2002/2003 constitutes a structural break in the data as first the 'old' BC50 was substituted by the (new) BC25, but re-introduced after a break of several months in winter 2002/2003. Thus, data collection starts in winter 2002/2003 with the introduction of the new loyalty card system. Our final dataset features about 300,000 BahnCards bought by almost 90,000 customers, with corresponding in-depth information on every transaction conducted by those customers over time, including purchase dates, prices paid, reductions obtained, travel departure and destination, asf.

5.2 Variables

The binary variable *PoS* indicates whether a BahnCard was bought via the Internet (*PoS* = 1) or via a counter (*PoS* = 0). We use customer *age* (in years), *gender* (1 – male, 0 – female), the *price* (in Euros) of BahnCard purchase (which varies for BC50 and BC25 contracts, and also due to price adjustments or promotions), and *region* dummies according to each customer's postal code. We control for purchases on workdays versus leisure days as counters may be closed on Sunday (1 – *Sunday*, 0 – workday), and for temporal effects using dummies per *quarter* (e.g., BahnCards may sell better in winter when road conditions are bad) and *year* (e.g., increasing environmental consciousness, changes in GDP or job market perspectives may affect changes in travel means).

We assess decision quality (the optimality of purchases) based on the simple cost-benefit approach described that generates 'optimality boundaries' for travel behavior. We consider the initial prices paid for the BahnCard and future investments in corresponding tickets for each customer, and record whether that customer would be better off if having chosen either a cheaper or a more expensive card instead of the existing one. Accordingly, each customer is assigned to one of the decision quality categories *optimal, suboptimal* or *beyond optimal* on an annual basis (see Appendix A).

Previous research in the context of behavioral loyalty studies argues that cancellation activity represents a particular suitable loyalty measure (Bolton, Kannan, and Bramlett 2000; Guillén et al. 2012; Xevelonakis and Som 2012). The variable *cancellation* (1 – cancellation occurs, 0 – otherwise) shows whether a customer maintains or cancels a BahnCard contract at the end of the operative period. Table 1 shows descriptive statistics. Tables 2 and 3 provide correlations.

		BC25		BC50	
Variable	**Description**	**Mean/Frequency for Binary Variables**	**Std. Dev.**	**Mean/Frequency for Binary Variables**	**Std. Dev.**
PoS	Internet (*PoS*=1), counter (*PoS*=0)	.1466	.3537	.2870	.4524
age	Customer age in years	42.3233	17.6616	41.7818	19.8404
gender	1 – male (m), 0 – female (f)	.4104	.4919	.4349	.4958
Price	BC purchase price	49.0502	17.4053	134.6074	48.0984
region0	Postal area codes	.0671	.2502	.0783	.2686
region1		.1138	.3176	.0935	.2911
region2		.1274	.3334	.1049	.3064
region3		.1202	.3252	.1332	.3398
region4		.0855	.2796	.0862	.2807
region5		.0994	.2992	.0971	.2961
region6		.1132	.3169	.1022	.3029
region7		.1145	.3184	.1163	.3206
region8		.0987	.2982	.1128	.3164
region9		.0602	.2379	.0754	.2641
Sunday	Sunday purchase (1 – yes, 0 – no)	.1078	.3102	.1330	.3395
quarter1	Controls for the quarter	.2963	.4567	.2011	.4009
quarter2	…	.3146	.4644	.1226	.3280
quarter3	…	.1859	.3890	.2603	.4388
quarter4	…	.2032	.4024	.4160	.4929
year2002	Controls for the year	.0295	.1693	0	0
year2003	…	.1950	.3962	.2183	.4131
year2004	…	.1763	.3811	.2019	.4014
year2005	…	.1849	.3882	.1736	.3788
year2006	…	.1754	.3803	.1734	.3786
year2007	…	.1866	.3896	.1730	.3783
year2008	…	.0519	.2218	.0594	.2365
sub_opt	Suboptimal usage (1 – yes, 0 – no)	.7383	.4396	.6151	.4866
byo_opt	Beyond optimal usage (1 – yes, 0 – no)	.0538	.2255	.0019	.0436
cancellation	Cancellation event (1 – yes, 0 – no)	.0767	.2662	.0943	.2923

Table 1. *Descriptive Statistics*

BC25	PoS	age	gender	price	region1	region2	region3	region4	region5	region6	region7	region8
PoS	1.0000											
age	-0.1697	1.0000										
gender	-0.0484	-0.1033	1.0000									
price	-0.1632	0.3367	-0.0185	1.0000								
region1	0.0110	-0.0115	0.0245	-0.0074	1.0000							
region2	-0.0135	0.0232	-0.0094	0.0063	-0.1355	1.0000						
region3	-0.0039	0.0204	-0.0104	-0.0195	-0.1301	-0.1443	1.0000					
region4	0.0065	0.0124	0.0085	0.0161	-0.1080	-0.1198	-0.1150	1.0000				
region5	-0.0040	0.0063	0.0053	0.0052	-0.1150	-0.1275	-0.1224	-0.1016	1.0000			
region6	-0.0065	-0.0092	0.0049	0.0106	-0.1225	-0.1359	-0.1305	-0.1083	-0.1153	1.0000		
region7	-0.0145	-0.0171	0.0007	-0.0197	-0.1265	-0.1403	-0.1347	-0.1118	-0.1190	-0.1268	1.0000	
region8	0.0058	-0.0142	-0.0097	-0.0020	-0.1164	-0.1291	-0.1239	-0.1028	-0.1095	-0.1167	-0.1204	1.0000
region9	0.0121	-0.0039	-0.0067	-0.0005	-0.0902	-0.1000	-0.0960	-0.0797	-0.0848	-0.0904	-0.0933	-0.0859

Table 2. *BC25: Correlations (Logistic Regressions)*

BC50	PoS	age	gender	price	region1	region2	region3	region4	region5	region6	region7	region8
PoS	1.0000											
age	0.1000	1.0000										
gender	-0.0032	-0.1077	1.0000									
price	0.0563	0.1049	-0.2040	1.0000								
region1	-0.0278	-0.0321	0.0212	0.0329	1.0000							
region2	-0.0151	0.0185	0.0074	0.0130	-0.1099	1.0000						
region3	-0.0083	0.0289	-0.0265	-0.0275	-0.1259	-0.1342	1.0000					
region4	-0.0018	0.0159	0.0115	-0.0029	-0.0986	-0.1051	-0.1204	1.0000				
region5	-0.0029	0.0262	-0.0005	-0.0015	-0.1053	-0.1123	-0.1286	-0.1007	1.0000			
region6	-0.0299	0.0209	0.0146	0.0341	-0.1084	-0.1155	-0.1323	-0.1036	-0.1107	1.0000		
region7	-0.0080	-0.0049	-0.0053	-0.0160	-0.1165	-0.1242	-0.1422	-0.1115	-0.1190	-0.1224	1.0000	
region8	0.0446	0.0006	-0.0155	0.0092	-0.1145	-0.1221	-0.1398	-0.1095	-0.1169	-0.1203	-0.1294	1.0000
region9	-0.0131	-0.0211	0.0013	-0.0245	-0.0917	-0.0978	-0.1120	-0.0877	-0.0937	-0.0964	-0.1036	-0.1018

Table 3. *BC50: Correlations (Logistic Regression)*

5.3 Methods

Descriptive Perspective (Point of Sale Choice).

Following a randomization of the dataset, we assign the sample cases to either a train dataset (80% of cases) or a test dataset (20%). Using the train dataset we apply logistic regression analysis, using *PoS* as the dependent variable. Customer *age*, *gender*, the *price* paid for the BahnCard and postal codes (*region*; *region0* is the baseline category) are independent variables. The interaction terms $age \times price$, $gender \times price$ and $region \times price$ are formed using mean-centered variables (Aiken and West 1991). We add the controls *Sunday* and dummies for each *quarter* (quarter 3 is the baseline category) and *year* (2008 is the baseline category; 2002 is excluded due to missing data for the BC50 sample):

$P(PoS = 1) = \frac{1}{1+e^{-z}}$, where

$$z = \beta_0 + \beta_1 * age + \beta_2 * gender + \beta_3 * price + \beta_4 * region1 + \cdots + \beta_{12} * region9 + \beta_{13} * region1 \times price + \cdots + \beta_{22} * region9\ x\ price + \beta_{22} * age \times price + \beta_{23} * gender \times price + \beta_{24} * sunday + \beta_{25} * quarter1 + \beta_{26} * quarter2 + \beta_{27} * quarter4 + \beta_{28} * year2003 + \cdots + \beta_{32} * year2007$$

For the train data, we estimate β-coefficients based on Maximum-Likelihood. Results for the BC25 sample are displayed in Table 4 (Table 5 for BC50). Then, we score the test data of BC25 and BC50 customers according to the obtained parameter estimates. To validate the scoring procedure in the test dataset, we run another logistic regression on PoS choice, this time using the respective score value as explanatory variable. The results provide evidence of appropriate model fit (for BC25 customers, Table 4; for BC50, Table 5). Moreover, Figure 5 shows the corresponding ROC (receiver operating characteristic) curve that illustrates the explanatory value of the classification method applied (Figure 6 for BC50). The ROC curve originates from signal detection theory (Egan 1975; Fawcett 2006) and is created by plotting the 'true positive' rate (sensitivity) against the 'false positive' rate (given by 1–specificity, where specificity = 'true negative' rate). Finally, we also assess the performance of our models via a classification method: To handle the trade-off between overall model accuracy and 'true positive' rate and ascertain that our models are valid and well-balanced, we define cut-off values based on the parameter estimates of the train data and classify the customers of the test dataset based on their score values (Metz 1978; Steyerberg et al. 2010). Accordingly, chi-square tests for independence between PoS choice and the classification results confirm the appropriateness of the prediction models for both BC25 (Pearson chi2(1) = 1.7e + 03; $p < 0.001$) and BC50 samples (Pearson chi2(1) = 2.0e + 03; $p < 0.001$; Mantel 1963).

Consumer Perspective and Firm Perspective (PoS, Decision Quality and Loyalty).

The analyses are based on customer age segments: *Youngsters*, age < 35; *Middle Agers*, 35 <= age < 50; *Seniors*, 50 <= age < 65; *Elderlies*, age >= 65 (Stanley, Ford, and Sande 1985; Tepper 1994). These segments are further divided into the subsegments *male* and *female*. Then, we apply chi-square tests in every customer segment and subsegment to determine whether PoS choice is related to a) *optimal, suboptimal* and *beyond optimal* BahnCard purchase, and b) *cancellation* activity (loyalty). In case of small cell frequencies, we apply additional Fisher-Yates tests (Finney 1948). In this context, the latter test provides more robust results than a chi-square test (although corresponding results do not differ in terms of significance levels in our sample). For both samples, and each segment and subsegment, we examine in which channel customers overall tend to achieve higher decision quality, based on probability calculations conditional on the chosen PoS. We also show the exact respective percentages of optimal buying decisions (conditional on PoS choice) reached by each customer (sub)segment. Further, we list the respective incidence of optimal and non-optimal decision quality as well as cancellation shares on an annual basis for both BC25 and BC50 customers (Table 8, 10) and across Internet and counter PoS (Table 9, 11).

6. Results

6.1 Descriptive Perspective

The regression analysis reveals that PoS choice depends on consumer-inherent demographic as well as contingent factors (supporting H1; see Tables 4, 5). For both BC25 and BC50 customers, *age* and *gender* have a significant influence on PoS choice, supporting hypotheses H1a and H1b. Higher age enhances the probability of an Internet purchase in the BC50 sample, but decreases Internet purchase in the BC25 sample. Being female enhances the probability for a counter purchase across both samples. *Regional* aspects contribute to explaining PoS choice as well (supporting H1c). PoS choice is also in part dependent on *pricing contexts* (here, we refer to both the different samples of BC50 and BC25 and the *price* variable as components of the 'pricing context'; for consumer and firm perspective analyses, for technical reasons we refer to the samples rather than the price variable): On the one hand, drivers of PoS choice differ across the (more expensive) BC50 and the (cheaper) BC25 samples, and on the other, a higher initial *price* for BahnCard purchase increases transactions via the Internet in the BC50 sample; even though price is insignificant in the BC25 sample (so we suggest these findings provide some support for H1d).

Almost all interaction terms are significant, yet their effects are different across the BC50 and BC25 samples. This supports the idea that the effect of pricing contexts on customers' PoS choice varies with age and gender (as proposed by H1e). In the BC50 sample, higher *price* and higher *age* together slightly increase the probability of an Internet purchase. This is interesting as previous research would have argued that older consumers tend to be both less technology affine and more risk-averse than young ones (Baltas, Argouslidis, and Skarmeas 2010; Guo 2001; Hitt and Frei 2002; Van Kenhove, de Wulf, and Van den Poel 2003), and probably encompass a lower proportion of Internet users anyway, so that more counter purchases would have been expected. A potential reason for the results observed here may be that those older consumers that engage in frequent travelling (which may also be indicated by choosing the more expensive BahnCard that grants higher reductions on subsequent fares) despite their high age may be particularly 'modern', affluent or mentally fit compared with their age group, and may thus be more inclined to collect information online and transact via e-commerce than cliché images of senior people would predict. Moreover, the probability of buying over the counter when being female decreases for high age BC50 customers. In the BC25 sample, higher prices weaken the negative effect of age and of being female on Internet PoS choice, which may be intuitive (despite the initially different influence of higher price on PoS choice, which may in part result from comparatively low variance in the BC25 price variable compared with the BC50 sample) if higher prices in the BC25 sample cause customer to behave more similar to the customers in the BC50 segment. A few of the *region* x *price* interaction terms are significant in both samples as well, indicating that some regions are more price-sensitive than others, yet we cannot observe a general geographical pattern. Furthermore, our tests applied as described in the methods section offer conclusive evidence that both models outperform any random models. Yet, model fit also suggests that additional factors may be interesting to study in explaining PoS choice (also due to its size, the dataset is limited to the variables described here).

6.2 Consumer Perspective

Concerning *purchase decision quality*, Tables 6 and 7 show that the percentages of both online and counter customers who use their BahnCard *optimally* is almost two times higher in the *high-price* context (BC50) than in the BC25 sample (almost every second customer versus every fourth for online purchases; more than four out of ten versus less than a quarter for counter purchases). Thus, as theory would predict customers seem to make more mature decisions if ‘more money is at risk’ and accordingly, display higher decision quality in high-price contexts (supporting H2a).

As regards demographics, in the BC50 sample decision quality decreases with *age*. For example, concerning online purchases (Table 7; 4th column, “Percentage P(opt=1| PoS=1)”), 51.04% of youngsters make optimal decisions (above sample average). Decision quality is lower for middle agers (46.42%) and seniors (44.06%), and considerably lower for elderlies (39.78%). Similar results apply to the BC25 sample (Table 6; 4th column, “Percentage P(opt=1| PoS=1)”): For online purchases, 32.97% of youngsters make optimal decisions (above sample average), and decision quality decreases for middle agers (33.28%, still above sample average), seniors (21.29%), and decreases drastically for elder people (7.03%). For counter purchases, youngsters behave optimally in 27.82% of cases (above sample average), decision quality increases slightly for middle agers (28.24%), but is reduced for seniors (18.27%), and strikingly low for elder people (4.24%).

Concerning *gender* effects, in the BC50 sample (Table 7; 4th column, “Percentage P(opt=1| PoS=1)”) decision quality in the Internet channel is generally higher when being female, which holds for all age groups other than elder people. For counter purchases (Table 7; 5th column, “Percentage P(opt=1| PoS=0)”), males tend to make better decisions across age groups. In the BC25 sample (Table 6; 4th column, “Percentage P(opt=1| PoS=1)”), males make better decisions in the Internet channel across all age groups other than middle agers. For counter purchases (Table 6; 5th column, “Percentage P(opt=1| PoS=0)”), male decision quality is higher across all groups (all t-tests with $p < 0.05$). Thus, H2b (“decision quality varies across segments”) is supported.

As regards the individual subsamples, taken together, male customers show higher decision quality than women in low-price contexts ($p < 0.05$), but female customers are better in high-price contexts if buying online ($p < 0.01$). These findings may lend support to the notion that women tend to display higher risk aversion, thus making more well-considered decisions in high-price, i.e. high-risk, contexts.

The chi-square tests also support that *PoS choice* and *decision quality* are significantly linked in both the BC25 and BC50 sample as well as in many of the segments and subsegments ($p < 0.05$) (Table 6, 4b; 6th columns, “Advantage* (customer perspective)”). First, in the BC50 sample, all segments and subsegments other than male youngsters tend to make better purchase decisions (in terms of the probability of making an ‘optimal’ decision) when buying online. The effect holds for the entire sample. Second, concerning customers that underuse their cards and thus would be better off with a cheaper one, suboptimal behavior is less frequent if choosing the online PoS (across subsegments other than male youngsters and female elderlies; 8th column, "Advantage# (customer perspective)"). Third, as regards those that overuse their cards and had better upgrade to a BC100, there are less significant results in the subsegments, but the entire BC50 sample and particularly, youngsters, less frequently overuse their cards when buying via the counter (10th column, "Advantage+ (customer perspective)"). Similar to the BC50 results, in the BC25 sample, first, the majority of segments and subsegments make optimal buying decisions rather when buying online instead of over the counter. The effect holds for the entire BC25 sample. Second, beyond optimal behavior is less frequent if choosing the Internet PoS, for the entire sample and particularly, for all the young and middle age segments and subsegments. Third, like in the BC50 case, young customers less frequently overuse their cards when buying via the counter. For the BC25 sample this effect extends to the middle agers as well. However, it does not hold for the entire BC25 sample, as seniors and elderlies tend to overuse their BahnCards less if buying online.

Summing up these results, choosing the Internet PoS significantly increases chances to realize high decision quality across most customer segments in both pricing contexts of BC50 and BC25. Therefore, we reject hypotheses H2 which suggested that decision quality should not depend on the PoS that customers prefer for their transactions.

As regards learning effects (H2c), Table 8 shows that the percentage of customers who exhibit optimal decision behavior in their BC25 choice has continuously grown (independently from pricing developments). In the high-price context of BC50, the increase in decision quality is even more pronounced (Table 10, 35% in 2003 to 57% in 2008). Thus, collective purchase decision quality of customers increases over time, lending support to hypothesis H2c.

Moreover, the strength of learning effects does not only depend on the pricing context, but on customer segments as well (for readability, here we focus on *gender* rather than adding further analyses of age effects). In the BC50 sample, learning effects in relation to customer segments in terms of gender differ as male customers seem to learn faster than their female counterparts. Even so, both optimality ratios settle down at similar levels (Table 10; columns "share opt: m" and "share opt: f"). However, in the BC25 sample (Table 8), the direction of learning effects is less balanced (men are significantly better (except for 2008); all $p < 0.01$). Next, we investigate whether learning effects depend on the chosen PoS. Tables 9 and 11 reveal the annual share of customers displaying optimal decision quality. We find that both Internet and counter customers show annual increases of decision quality. This effect holds for both BC50 and BC25 samples. In the BC50 sample, the magnitude of learning effects across the two points of sale is quite comparable. In the BC25 sample however, Internet buyers show stronger learning effects than counter customers ($p < 0.001$). Therefore, H2d is supported as the increase in decision quality varies across pricing contexts and segments; yet other than expected, this increase also varies slightly across PoS.

6.3 Firm Perspective

Chi-square tests reveal that PoS choice is associated with customer loyalty for both the BC25 and BC50 samples as proposed by H3 (Tables 6, 7; second but last column, "Linkages between PoS and Cancellation"). In the BC50 sample, customers continue their purchase behavior more often if buying via the Internet. This holds for the entire BC50 sample (Table 7; last column, "Advantage~ (firm perspective)") and concerning (sub)segments, for all middle agers, for female seniors, and for all elder customers. In the BC25 sample (Table 6), online purchasing is related to significantly lower cancellation activity, overall and particularly, in the youngster segment and for elder people, particularly, females (annual comparisons as displayed by Table 9 are mostly insignificant). Moreover, when comparing the relation of cancellation events and PoS choice in the high price context (Table 11), cancellation activity turns out to be significantly higher among counter buyers, as t-tests on an annual basis show ($p < 0.001$). Interestingly, this result is contrary to most studies discussing customer loyalty as these often argue that counter customers would be more loyal than online customers. However, the finding is in line with results observed by Shankar, Smith, and Rangaswamy (2003).

As proposed by H3a, loyalty also varies across pricing contexts (Tables 8, 10 show some differences in cancellation rates across the two samples). Cancellation rates vary over the years and take a rather u-shaped form in the BC25 segment, whereas the u-shape is inverted in the BC50 segment, with sharply decreasing cancellation rates in the final year of the sample data. Considering the available data, BC25 customers are overall slightly less loyal than BC50 customers ($p < 0.05$). However, loyalty depends only marginally on customer segments in terms of gender (Table 10; columns “Share cancel: m” and “Share cancel: f” rarely show significant differences) and if so, rather in the BC25 sample, where female customers appear to cancel their contracts more often than male customers (Table 8; $p < 0.10$ after 2003; offering only little support for H3b). Furthermore, customer loyalty does depend on previous decision quality, as proposed by H3c. Additional Chi-square tests reveal that in a few BC25 subsegments, but across all subsegments in the BC50 context, optimal contract choice is associated with (lower; as indicated by additional regressions of contract choices on subsequent cancellations) cancellation activity ($p < 0.001$).

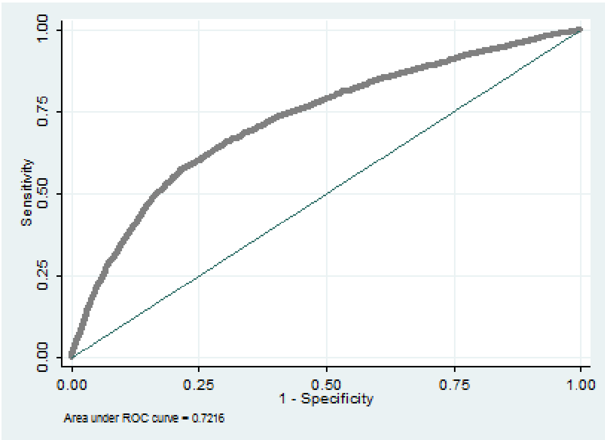


Figure 5. *ROC Curve – Logistic Regression: BC25 Customers (Test Data)*

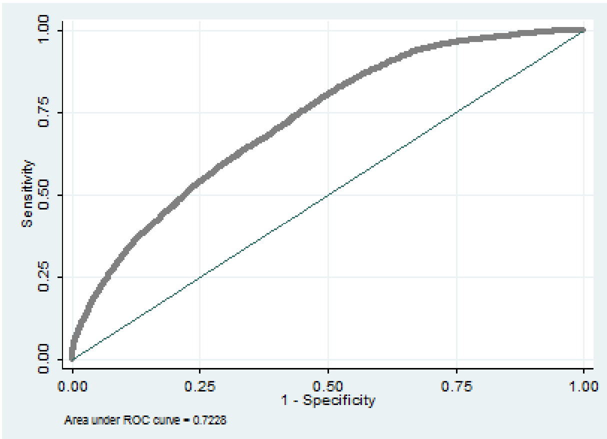


Figure 6. *ROC Curve – Logistic Regression: BC50 Customers (Test Data)*

Train Data	Coefficient	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
age ***	-.0257	.0029	-8.77	0.000	-.03150	-.0200
gender **	-.2871	.0920	-3.12	0.002	-.4673	-.1069
price	-.0026	.0018	-1.45	0.146	-.0060	.0009
region1	.0638	.0439	1.45	0.146	-.0222	.1498
region2 **	-.1307	.0433	-3.02	0.003	-.2154	-.0459
region3 *	-.0942	.0436	-2.16	0.031	-.1795	-.0088
region4	.0087	.0460	0.19	0.850	-.0815	.0989
region5	-.0038	.0451	-0.08	0.932	-.0922	.0845
region6 †	-.0752	.0445	-1.69	0.091	-.1624	.0120
region7 **	-.1217	.0444	-2.74	0.006	-.2086	-.0347
region8	.0209	.04480	0.47	0.640	-.0669	.1087
region9	.0582	.0494	1.18	0.238	-.0385	.1550
age×price ***	.0008	.0001	15.17	0.000	.0007	.0009
gender×price ***	.0102	.0017	6.03	0.000	.0069	.0135
sunday ***	.1317	.0287	4.58	0.000	.0754	.1880
quarter1 ***	-.2179	.0260	-8.37	0.000	-.2689	-.1669
quarter2 ***	-.2735	.0257	-10.66	0.000	-.3238	-.2232
quarter4 ***	-.6381	.0351	-18.19	0.000	-.7069	-.5694
year2003 ***	.2563	.0468	5.47	0.000	.1644	.3481
year2004 ***	-.7180	.0601	-11.94	0.000	-.8358	-.6002
year2005 ***	-.2858	.0571	-5.00	0.000	-.3977	-.1738
year2006 ***	-.3186	.0609	-5.24	0.000	-.4379	-.1994
year2007	-.0935	.0622	-1.50	0.133	-.2153	.0283
_cons	-2.0879	.1112	-18.78	0.000	-2.3058	-1.870

Number of obs = 92030 LR chi2(24) = 7249.41 Pseudo R2 = 0.2857

Test Data	Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
score ***	7.3023	.1646	44.37	0.000	6.9797	7.6248
_cons	-3.0205	.0409	-73.82	0.000	-3.1007	-2.9403

Number of obs = 23013 LR chi2(24) = 2134.47 Pseudo R2 = 0.2008

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. All *region* x *price* dummies are included in the regression, yet not shown for table readability, as result are inconclusive.

Table 4. *BC25: Logistic Regression*

Train Data	Coefficient	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
age ***	.0163	.0014	11.77	0.000	.0136	.0190
gender *	-.1161	.0575	-2.02	0.044	-.2289	-.0033
price *	.0011	.0005	2.17	0.030	.0001	.0022
region1 ***	-.2621	.0348	-7.54	0.000	-.3302	-.1940
region2 ***	-.1963	.0336	-5.85	0.000	-.2621	-.1306
region3 ***	-.1769	.0318	-5.56	0.000	-.2393	-.1145
region4 **	-.1078	.0347	-3.11	0.002	-.1758	-.0398
region5 ***	-.1266	.0337	-3.75	0.000	-.1928	-.0605
region6 ***	-.3402	.0341	-9.97	0.000	-.4071	-.2734
region7 **	-.1094	.0325	-3.37	0.001	-.1730	-.0458
region8 **	.0903	.0322	2.80	0.005	.0272	.1534
region9	-.0211	.0355	-0.60	0.551	-.0907	.0484
age×price ***	.0001	.0000	3.37	0.001	.0000	.0001
gender×price *	.0006	.0003	2.08	0.037	.0000	.0012
sunday **	.0574	.0207	2.77	0.006	.0168	.0981
quarter1 **	-.0611	.0222	-2.75	0.006	-.1047	-.0176
quarter2 ***	-.6513	.0272	23.96	0.000	-.7045	-.5980
quarter4 ***	.8992	.0191	47.14	0.000	.8618	.9366
year2003 ***	-2.8105	.0419	-67.04	0.000	-2.8926	-2.7283
year2004 ***	-1.6721	.0390	-42.82	0.000	-1.7486	1.5956
year2005 ***	-1.3664	.0408	-33.52	0.000	-1.4463	-1.2866
year2006 ***	1.0289	.0410	-25.09	0.000	-1.1093	-.9486
year2007 ***	-.6062	.0412	-14.70	0.000	-.6870	-.5253
_cons	-.4892	.0794	-6.16	0.000	-.6447	-.3337

Number of obs = 111888 LR chi2(24) = 14632.80 Pseudo R2 = 0.2901

Test Data	Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
score ***	4.824572	.0872426	55.30	0.000	4.65358	4.995565
_cons	-2.39754	.0315536	-75.98	0.000	-2.459384	-2.335696

Number of obs = 27972 LR chi2(24) = 3481.59 Pseudo R2 = 0.1937

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. All *region* x *price* dummies are included in the regression, yet not shown for table readability, as result are inconclusive.

Table 5. *BC50: Logistic Regression*

Segments	**Subseg-ments**	**Linkages between PoS and Optimal Usage**	**Percentage** P(opt=1| PoS=1) in %	**Percentage** P(opt=1| PoS=0) in %	**Advantage*** (customer perspective)	**Linkages between PoS and Suboptimal Usage**	**Advantage#** (customer perspective)	**Linkages between PoS and Over-Usage**	**Advantage+** (customer perspective)	**Linkages between PoS and Cancella-tion**	**Advantage~** (firm per-spective)
BC25 (all)	-	✓	25.78	23.96	**Internet**	✓	**Internet**	**X**	-	✓	**Internet**
Youngsters	-	✓	32.97	27.82	**Internet**	✓	**Internet**	✓	**Counter**	✓	**Internet**
Youngsters	Female	**X**	30.10	26.88	**-**	✓	**Internet**	✓	**Counter**	✓	**Internet**
Youngsters	Male	✓	36.01	29.07	**Internet**	✓	**Internet**	✓	**Counter**	✓	**Internet**
Middle Agers	-	✓	33.28	28.24	**Internet**	✓	**Internet**	✓	**Counter**	**X**	**-**
Middle Agers	Female	✓	35.20	27.46	**Internet**	✓	**Internet**	✓	**Counter**	**X**	**-**
Middle Agers	Male	**X**	31.75	29.18	**-**	✓	**Internet**	✓	**Counter**	**X**	**-**
Seniors	-	✓	21.29	18.27	**Internet**	**X**	**-**	✓	**Internet**	**X**	**-**
Seniors	Female	**X**	18.68	16.10	**-**	**X**	**-**	✓	**Internet**	**X**	**-**
Seniors	Male	**X**	24.59	22.28	**-**	**X**	**-**	**X**	-	**X**	**-**
Elderlies	-	✓	7.03	4.24	**Internet**	**X**	**-**	✓	**Internet**	✓	**Internet**
Elderlies	Female	✓	5.66	3.43	**Internet**	**X**	**-**	✓	**Internet**	✓	**Internet**
Elderlies	Male	**X**	10.10	6.80	**-**	**X**	**-**	✓	**Internet**	**X**	**-**

* Comparison of conditional probabilities: P(opt=1| PoS=0) vs. P(opt=1| PoS=1) → criterion: “>”
\# Comparison of conditional probabilities: P(suboptimal=1| PoS=0) vs. P(suboptimal=1| PoS=1) → criterion: “<”
\+ Comparison of conditional probabilities: P(beyond optimal=1| PoS=0) vs. P(beyond optimal=1| PoS=1) → criterion: “<”
~ Comparison of conditional probabilities: P(cancellation=1| PoS=0) vs. P(cancellation=1| PoS=1) → criterion: “<”.

Table 6. *BC25: Results of the Chi2-Tests*

Segments	**Subseg-ments**	**Linkages between PoS and Optimal Usage**	**Percentage** P(opt=1| PoS=1) in %	**Percentage** P(opt=1| PoS=0) in %	**Advantage*** (customer perspective)	**Linkages between PoS and Suboptimal Usage**	**Advantage#** (customer perspective)	**Linkages between PoS and Over-Usage**	**Advantage+** (customer perspective)	**Linkages between PoS and Cancella-tion**	**Advantage~** (firm per-spective)
BC50 (all)	-	✓	47.13	41.48	**Internet**	✓	**Internet**	✓	**Counter**	✓	**Internet**
Youngsters	-	✓	51.04	47.36	**Internet**	✓	**Internet**	✓	**Counter**	**X**	**-**
Youngsters	Female	✓	52.23	46.58	**Internet**	✓	**Internet**	✓	**Counter**	**X**	**-**
Youngsters	Male	**X**	49.54	48.29	**-**	**X**	**-**	✓	**Counter**	**X**	**-**
Middle Agers	-	✓	46.42	37.93	**Internet**	✓	**Internet**	**X**	**-**	✓	**Internet**
Middle Agers	Female	✓	47.70	35.29	**Internet**	✓	**Internet**	**X**	**-**	✓	**Internet**
Middle Agers	Male	✓	45.53	39.89	**Internet**	✓	**Internet**	**X**	**-**	✓	**Internet**
Seniors	-	✓	44.06	35.04	**Internet**	✓	**Internet**	**X**	**-**	✓	**Internet**
Seniors	Female	✓	45.06	32.47	**Internet**	✓	**Internet**	**X**	**-**	✓	**Internet**
Seniors	Male	✓	42.66	38.78	**Internet**	✓	**Internet**	**X**	-	**X**	-
Elderlies	-	✓	39.78	24.96	**Internet**	✓	**Internet**	**X**	**-**	✓	**Internet**
Elderlies	Female	✓	37.97	21.88	**Internet**	**X**	**-**	✓	**Internet**	✓	**Internet**
Elderlies	Male	✓	44.44	31.99	**Internet**	✓	**Internet**	**X**	**-**	✓	**Internet**

* Comparison of conditional probabilities: P(opt=1| PoS=0) vs. P(opt=1| PoS=1) → criterion: “>”
# Comparison of conditional probabilities: P(suboptimal=1| PoS=0) vs. P(suboptimal=1| PoS=1) → criterion: “<”
+ Comparison of conditional probabilities: P(beyond optimal=1| PoS=0) vs. P(beyond optimal=1| PoS=1) → criterion: “<”
~ Comparison of conditional probabilities: P(cancellation=1| PoS=0) vs. P(cancellation=1| PoS=1) → criterion: “<”.

Table 7. *BC50: Results of the Chi2-Tests*

Year	Average Price	Share opt	Share non_opt	Share cancel	Share opt: m	Share opt: f	Share cancel: m	Share cancel: f
2002	48.8128	0.2470	0.7530	0.1737	.2844	.2180	.1794	.1695
2003	50.6934	0.2326	0.7674	0.1678	.2731	.2047	.1672	.1677
2004	44.1237	0.2064	0.7936	0.1763	.2275	.1915	.1711	.1800
2005	46.8820	0.2120	0.7880	0.1359	.2244	.2034	.1281	.1416
2006	46.5155	0.2712	0.7288	0.1757	.2815	.2641	.1673	.1816
2007	45.4857	0.2840	0.7160	0.1862	.3041	.2739	.1701	.2005
*2008	48.7840	0.3469	0.6531	-	.3534	.3442	-	-

*Note: *Cancellation* activity for 2008 is not studied as data are left-censored (i.e. cancellation activity cannot be observed for the entire year 2008). Results on decision quality are based on an extrapolation of behavior observed until July 2008.

Table 8. *BC25: Learning Effects and Cancellation Activity*

PoS=0

Year	Average Price	Share opt	Share non_opt	Share cancel
2002	58.3582	0.2537	0.7463	0.1740
2003	56.8910	0.2214	0.7786	0.1760
2004	46.7273	0.2582	0.7418	0.1759
2005	47.9430	0.2927	0.7073	0.1375
2006	48.1253	0.3212	0.6788	0.1821
2007	40.6609	0.3438	0.6562	0.1919
*2008	44.6161	0.3116	0.6884	-

PoS=1

Year	Average Price	Share opt	Share non_opt	Share cancel
2002	47.6717	0.2462	0.7538	0.1716
2003	49.2262	0.2352	0.7648	0.1335
2004	43.9163	0.2023	0.7977	0.1818
2005	46.7656	0.2031	0.7969	0.1218
2006	46.3147	0.2649	0.7351	0.1241
2007	46.3397	0.2735	0.7265	0.1452
2008	49.8328	0.3542	0.6458	-

*Note: *Cancellation* activity for 2008 is not studied as data are left-censored (i.e. cancellation activity cannot be observed for the entire year 2008). Results on decision quality are based on an extrapolation of behavior observed until July 2008.

Table 9. *BC25: Learning Effects and Loyalty related to Point of Sale*

Year	Average Price	Share opt	Share non_opt	Share cancel	Share opt: m	Share opt: f	Share cancel: m	Share cancel: f
*2002	-	-	-	-	-	-	-	-
2003	130.7686	0.3527	0.6473	.1222	.3867	.3285	.1252	.1199
2004	131.8937	0.3727	0.6273	.1856	.4045	.3479	.1900	.1821
2005	132.3499	0.4399	0.5601	.1659	.4459	.4350	.1689	.1634
2006	136.2422	0.4650	0.5350	.1905	.4624	.4672	.1871	.1934
2007	139.1215	0.5300	0.4700	.1141	.5294	.5314	.1165	.1118
2008	153.4854	0.5666	0.4334	-	.5719	.5626	-	-

*Note: BC50 was (re)introduced later than BC25 in winter 2002/2003, there is no data for 2002. *Cancellation* activity for 2008 is not studied as data are left-censored (i.e. cancellation activity cannot be observed for the entire year 2008). Results on decision quality are based on an extrapolation of behavior observed until July 2008.

Table 10. *BC50: Learning Effects and Cancellation Activity*

PoS=0

Year	Average Price	Share opt	Share non_opt	Share cancel
*2002	-	-	-	-
2003	141.5240	0.3026	0.6974	0.1240
2004	133.2632	0.4051	0.5949	0.1964
2005	133.3612	0.4738	0.5262	0.1760
2006	137.7170	0.4973	0.5027	0.1981
2007	137.5623	0.5392	0.4608	0.1303
2008	149.1508	0.5359	0.4641	-

PoS=1

Year	Average Price	Share opt	Share non_opt	Share cancel
*2002	-	-	-	-
2003	128.8874	0.3614	0.6386	0.1115
2004	131.3194	0.3591	0.6409	0.1597
2005	131.7227	0.4188	0.5812	0.1496
2006	135.1059	0.4401	0.5599	0.1807
2007	140.5441	0.5215	0.4785	0.0963
2008	157.8226	0.5938	0.4062	-

*BC50 was (re)introduced later than BC25 in winter 2002/2003, there is no data for 2002. *Cancellation* activity for 2008 is not studied as data are left-censored (i.e. cancellation activity cannot be observed for the entire year 2008). Results on decision quality are based on an extrapolation of behavior observed until July 2008.

Table 11. *BC50: Learning Effects and Loyalty related to Point of Sale*

7. Discussion

The question of how customers' characteristics drive the use of online purchasing versus the use of traditional channels, and how different channels are related to consumer behavior and loyalty, remains surprisingly unanswered to date (Brown and Dant 2009; Hitt and Frei 2002; Homburg, Hoyer, and Fassnacht 2002; Reinartz, Krafft, and Hoyer 2004; Wallace, Giese, and Johnson 2004). Here, we shed light on these issues and add new insights to the literature investigating multichannel distribution. Our results provide for a better understanding of the linkages between customer heterogeneity, decision quality and loyalty behavior, which is important for retailers that combine distribution channels, and for allocating resources effectively across and within channels. A more detailed grasp of this context is also essential when discussing the effectiveness of loyalty-creating approaches, and if proposing business strategies matched to future market development.

First, results from our descriptive analyses show that various consumer-inherent and contingent factors affect PoS choice. Demographic factors like age and gender influence PoS preferences, as does the pricing context. Interestingly, higher customer age is positively related to Internet purchasing in high-price contexts, whereas it is negatively related to Internet purchasing in low-price contexts. Interaction effects demonstrate that across pricing contexts, the preference for Internet purchasing increases (or the preference for counter purchases decreases) with customer age and across genders if the initial price for acquiring a loyalty card is comparably high.

Second, taking a consumer perspective, we can establish that consumers' purchase decision quality is in fact dependent on the chosen PoS. Overall, customers tend to make better decisions if choosing Internet transactions (in terms of the conditional probabilities P(optimal = 1| PoS = 0) and P(optimal = 1| PoS = 1). Customers who tend to overestimate their subsequent use of their loyalty card are also generally better off in choosing the Internet channel (conditional probabilities P(suboptimal = 1| PoS = 0) and P(suboptimal = 1| PoS = 1)). Younger and medium-aged customers who tend to underestimate their card usage are better off in visiting a counter for deciding on transactions, yet older consumers who underestimate card usage tend to display higher decision quality in Internet channels (conditional probabilities P(beyond optimal = 1| PoS = 0) and P(beyond optimal = 1| PoS = 1)). Additionally, decision quality largely varies across pricing contexts, with significantly better decisions being made in high-price settings, and across customer segments, where higher age is strongly associated with substantially lower decision quality. Moreover, decision quality of male consumers is generally higher across pricing contexts and across PoS choices, but women achieve better results in high-price Internet purchases. However, learning effects over time are considerable, although their strength differs across low- and high-price contexts as well as across customer segments and PoS. In high-price contexts, both genders experience similar learning effects over time, in low-price contexts, learning accelerates for male customers rather than females. Collective learning rates are higher in Internet purchasing.

Third, assuming a company perspective, we study whether customer loyalty depends on PoS choice. Our results highlight that overall, Internet customers are more loyal than counter customers. Loyalty is higher in high price contexts, marginally higher if customers are male, and intuitively, is higher if decision quality has proven perfect. Table 12 summarizes the central findings.

Perspective	Focus	Hypothesis	Result	Summary of Central Findings
Descriptive:	PoS Choice	*H1 Consumer-inherent as well as contingent factors determine customers' point of sale choice.*	✓	*Customer heterogeneity affects outcomes of retail strategies that combine distribution channels, and is important for allocating resources effectively across/within channels.*
		H1a Customers' point of sale choice varies with age.	✓	Contrary to what previous studies would predict, higher age can in fact concur with preferences for using online instead of traditional channels.
		H1b Customers' point of sale choice varies across genders.	✓	Female customers prefer traditional channels.
		H1c Customers' point of sale choice varies across regions.	✓	Regional aspects drive PoS choice, eventually due to differences in socio-economic patterns and available infrastructure.
		H1d Customers' point of sale choice varies across high- and low-price contexts.	Partly Confirmed	Internet purchase is generally preferred in high-price contexts, PoS choice can vary otherwise.
		H1e The effect of pricing contexts on customers' point of sale choice varies with age, gender, and across geographical regions.	✓	Higher prices increase tendencies for purchasing online particularly among older customers, and decrease counter preferences in female customers. (Effects depend on regional aspects as well.)
Consumer:	Purchase Decision Quality	*H2 The quality of consumers' purchase decisions does not depend on online versus offline point of sale choice.*	Rejected	*Despite opportunities for acquiring information relevant for purchase decisions at either PoS, decision quality is much higher in online channels.*
		H2a Purchase decision quality varies across low- and high-price contexts.	✓	Decision quality is much higher in high-price contexts.
		H2b Purchase decision quality varies across customer segments.	✓	Decision quality decreases with age. Decision quality of male customers is usually higher. (Female customers make better decisions only in high-price online settings.)
		H2c Purchase decision quality increases over time.	✓	As time passes, customers experience collective learning effects.
		H2d The increase in purchase decision quality varies across low- and high-price contexts and across customer segments, but not across points of sale.	Partly Confirmed	Learning accelerates in high price contexts. Male customers learn slightly faster. Customers choosing online channels tend to learn faster.
Firm:	Customer Loyalty	*H3 Customer loyalty depends on online versus offline point of sale choice.*	✓	*Contrary to what previous studies would predict, customer loyalty is higher in online channels compared with traditional channels.*
		H3a Customer loyalty varies across low- and high-price contexts.	✓	Loyalty is higher in high-price contexts.
		H3b Customer loyalty varies across customer segments.	Partly Confirmed	Male customers are marginally more loyal than female customers.
		H3c Customer loyalty varies with purchase decision quality.	✓	Loyalty increases with decision quality.

Table 12. *Summary of Results*

7.1 Theoretical Implications

Grewal and Levy (2009) argue that four topics will provide the greatest future contribution to retailing literature: the growth of the Internet and e-commerce, customer loyalty, service success strategies, and behavioral issues in pricing and patronage. By integrating these topics and studying their overlap, we strive to provide some insights to multichannel research. Some of our findings are contrary to what previous studies would predict.

First, few studies have explicitly focused on how customer heterogeneity is related to online versus offline distribution (Hitt and Frei 2002; Tsai and Lee 2009; Varian and Shapiro 1998). We show how customer heterogeneity is related to either PoS and to subsequent purchase behavior. Second, although customer satisfaction with purchase decisions is extensively studied, decision quality is not, although it would complement satisfaction research by providing an objective and less volatile assessment of purchase advantageousness. Two-part pricing contracts offer a prime opportunity for such objective assessments. We study under what conditions customers tend to make better buying decisions and offer some insights into the potential scope and the benefits of learning effects. Third, whereas previous studies have often focused on service experiences or (dis)satisfaction as driving outcomes in loyalty programs, we broaden the picture by highlighting linkages between consumer-inherent and contingent factors, decision quality, and PoS choice. Besides, to date, few studies investigate determinants of consumer responsiveness towards such programs, particularly, using large-scale datasets (Bolton, Kannan, and Bramlett 2000; Keh and Lee 2006; Kivetz and Simonson 2003). There is also a lack of research into two-part pricing systems, although such schemes are increasingly used and are particularly intended to create loyalty.

7.2 Methodological Implications

First, we advance the external validity of previous studies on multichannel distribution and loyalty programs by testing our hypotheses based on an extensive, proprietary, longitudinal dataset from one of the largest German loyalty programs. Thereby, we can offer robust insights into the directions and magnitudes of the effects under study. Second, since we examined an entire population of travel service customers in the biggest European economy, we suggest that findings may be transferable to similar economic settings: Extending the focus beyond the current study context, results may help forecast customer behavior towards multichannel strategies for suppliers of comparable services where consumers find it hard to quantify their future demand accurately (e.g., financial/insurance/legal services, education services, club memberships, car-sharing contracts), and may offer guidance for firms applying two-part pricing schemes in general (e.g., concerning customer segmentation, channel responsiveness, decision quality and learning). Findings (e.g., demographic effects) may also apply to similar travel services contexts where both online and offline distribution are the norm (e.g., travel agents, hotels, rental cars).

7.3 Managerial Implications

The coordination of online and offline channels is of particularly compelling interest to both researchers and practitioners. First, identifying the selection criteria of Internet vis-à-vis counter purchase environments should help retailers design more effective strategies for customer acquisition and customer retention, which is obviously strongly linked to profitability. Acquisition strategies in both channels are clearly more efficient if tailored to those customer segments that actually prefer the respective channel. For example, in high-price contexts older consumers prefer online purchases, which may be counterintuitive but next implies that resources invested at offline PoS into trying attract seniors to the offering could make more impact elsewhere. Second, given that both Internet usage and population age are on the increase, the effect of pricing contexts on PoS choice indicates a decreasing importance of traditional channels for high-price offerings. This has implications for reorganizing and balancing the company mix of online versus offline purchase opportunities, particularly when introducing more expensive pricing schemes or additional quality services.

Third, our results inform e-commerce strategy by establishing how the behavior of customers subsequent to PoS choice differs across the two most important channels. Our results affirm significant differences in terms of the initial quality of purchase decisions reached, of learning effects realized, as well as of loyalty displayed. Concerning decision quality, although the Internet is recognized as an ineffective means for communicating reliable and informative cues in various contexts (Berthon et al. 1999; Laroche et al. 2005), the results indicate that using online channels does not necessarily make the purchase of travel services, or of two-part pricing contracts, any more difficult to evaluate for consumers. In fact, most customers are better off if engaging in Internet instead of counter purchasing. We provide a detailed record under what conditions which customer segments tend to make better purchase decisions. On the one hand, the analyses offer insights into the potential benefits consumers could generate by critical re-evaluations of their individual purchase behavior and by striving for learning effects. Yet, decision quality is essential to both parties to the contract, i.e., consumers and retailers. As the analyses show, the precision of customers' demand forecasts and the resulting purchase decisions are quite often 'off the mark'. On a first impulse, this 'overconfidence' of consumers in estimating their future needs may create an incentive for firms, monopolists and competitive firms alike, to offer tariffs that make use of this inability (Grubb 2009). However, firms may also benefit from enabling consumers to make better forecasts (e.g., due to better information provision by the retailer or opportunities to downgrade at regular intervals) in the long run, as the results suggest that customers reaching high decision quality are much more loyal to the firm.

Fourth, as still many programs do not produce the outcomes desired by the firm and as managers and academics become increasingly interested in the 'true' value of customer loyalty programs (Ellinger, Daugherty, and Gustin 1997; Ellinger, Daugherty, and Plair 1999; Ramanathan 2010; Steven 2012), we can offer some insights into customer responsiveness based on customer segments, pricing contexts and decision quality. Consequently, optimizing communication efforts directed at consumers may be an effective means across channels to induce learning effects and thereby, increase customer loyalty. For example, in online settings, it might be profitable to offer customer testimonials to help develop a better understanding of the offering (Weathers, Sharma, and Wood 2007; Wind and Rangaswamy 2001), to personalize sites according to customer segments and information needs, as well as to increase social interaction features that promote social learning among customers and bind them to the firm. Based on the detailed documentation of linkages between consumer characteristics, PoS preferences, purchase decision quality, and customer loyalty, our results would help retail firms assess the potential effects of promoting, re-developing, and fine-tuning their two-part pricing schemes on consumers' subsequent purchase behavior, both initially and over extended periods.

7.4 Limitations and Further Research

The availability of electronic data sets that contain information about linkages between people and product or service sales provides researchers with an unprecedented microscopic view into the interdependencies and contingencies affecting consumers' buying decisions (Oestreicher-Singer and Sundararajan 2010). As limitations to this research, we could not study decision processes in detail. Apart from analyzing complementarities between, or the relative importance of, a combination of our demographic and other socio-economic variables (e.g., household wealth) and consumer traits (e.g., susceptibility to social influence, environmental consciousness) during the evolution of purchase processes, further research could also focus on effects of the evolution of firms' online and offline marketing practices and consumers' choices. Second, we recognize that customers are to some extent intrinsically different in the predisposition to being loyal, as perceptions of costs and benefits vary among customers (Baltas, Argouslidis, and Skarmeas 2010). Future research could also study approaches that are specifically suited to counter disloyalty in online and in offline channels. Besides, our research is situated in the context of *travel* services; other relevant settings can yield additional insights into aspects driving channel preferences, learning and customer loyalty (Brown and Dant 2011). An integrated analysis of such complex patterns of purchase behavior may warrant a combination of large-scale observational and survey data to offer greater detail on driving forces of what appears to be identical behavior.

8. References

Aiken, Leona S., and Stephen G. West (1991). *Multiple regression: Testing and interpreting interactions*. Newbury Park, CA: Sage.

Allaway, Arthur W., Richard M. Gooner, David Berkowitz, and Lenita Davis (2006). Deriving and exploring behavior segments within a retail loyalty card program. *European Journal of Marketing*, 40(11–12), 1317–1339.

Allender, William J., and Timothy J. Richards (2012). Brand loyalty and price promotion strategies: An empirical analysis. *Journal of Retailing*, 88(3), 323–342.

Anderson, Chris (2006). *The long tail: Why the future of business is selling less of more*. New York: Hyperion.

Bailey, Joseph P., and J. Yannis Bakos (1997). An exploratory study of the emerging role of electronic intermediaries. *International Journal of Electronic Commerce*, 1(3), 7–20.

Bakos, J. Yannis (1991). A strategic analysis of electronic marketplaces. *MIS Quarterly*, 15(3), 295–310.

Bakos, J. Yannis (1997). Reducing buyer search costs: Implications for electronic marketplaces. *Management Science*, 43(12), 1676–1692.

Baltas, George, Paraskevas C. Argouslidis, and Dionysis Skarmeas (2010). The role of customer factors in multiple store patronage: A cost–benefit approach. *Journal of Retailing*, 86(1), 37–50.

Barber, Brad M., and Terrance Odean (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, 55(2), 773–806.

Bart, Yakov, Venkatesh Shankar, Fareena Sultan, and Glen L. Urban (2005). Are the drivers and role of online trust the same for all web sites and consumers? A large-scale exploratory empirical study. *Journal of Marketing*, 69(4), 133–152.

Bauer, Raymond A. (1960). Consumer behavior at risk taking, in: Donald F. Cox (ed.), *Risk taking and information handling in consumer behavior*. Boston, MA: Harvard University Press.

Baumgartner, Hans, and Jan-Benedict E.M. Steenkamp (1996). Exploratory consumer buying behavior: Conceptualization and measurement. *International Journal of Research in Marketing*, 13(2), 121–137.

Baumol, William J., and Richard E. Quandt (1964). Rules of thumb and optimally imperfect decisions. *American Economic Review*, 54(2), 23–46.

Bearden, William O., and Terence A. Shimp (1982a). The use of extrinsic cues to facilitate product adoption. *Journal of Marketing Research*, 19(2), 229–239.

Bearden, William O., and Terence A. Shimp (1982b). Warranty and other extrinsic cue effects on consumers' risks perceptions. *Journal of Consumer Research*, 9(1), 38–46.

Berman, Barry (2006). Developing an effective customer loyalty program. *California Management Review*, 49(1), 123–148.

Berthon, Pierre, Leyland Pitt, Constantine S. Katsikeas, and Jean Paul Berthon (1999). Virtual services go international: International services in the marketspace. *Journal of International Marketing*, 7(3), 84–105.

Bolton, Ruth N., P.K. Kannan, and Matthew D. Bramlett (2000). Implications of loyalty program membership and service experiences for customer retention and value. *Journal of the Academy of Marketing Science*, 28(1), 95–108.

Brown, James R., and Rajiv P. Dant (2011). The Journal of Retailing 2006-2011: A nostalgic retrospective. *Journal of Retailing*, 87(4), 419–426.

Brown, James R., and Rajiv P. Dant (2009). The theoretical domains of retailing research: A retrospective. *Journal of Retailing*, 85(2), 113–128.

Brynjolfsson, Erik, and Michael D. Smith (2000). Frictionless commerce? A comparison of internet and conventional retailers. *Management Science*, 46(4), 563–585.

Clemons, Eric K., and Michael C. Row (1992). Information technology and industrial cooperation: The role of changing transaction costs. *Journal of Management Information Systems*, 9(2), 9–28.

Clemons, Eric K., Il-Horn Hann, and Lorin M. Hitt (1999). The nature of competition in electronic markets: An empirical investigation of online travel agent offerings. The Wharton School of the University of Pennsylvania: Working paper.

Cox, Donald F., and Stuart U. Rich (1964). Perceived risk and consumer decision-making: The case of telephone shopping, in: Donald F. Cox (ed.), *Risk Taking and Information Handling in Consumer Behavior.* Boston, MA: Harvard University Press.

Day, George S. (1969). A two-dimensional concept of brand loyalty. *Journal of Advertising Research*, 9(3), 29–35.

De Berranger, Pascale, and Mary C. R. Meldrum (2000). The development of intelligent local clusters to increase global competitiveness and local cohesion: The case of small businesses in the creative industries. *Urban Studies*, 37(10), 1827–1835.

Dowling, Grahame R., and Richard Staelin (1994). A model of perceived risk and intended risk-handling activity. *Journal of Consumer Research*, 21(1), 119–134.

Egan, James P. (1975). *Signal detection theory and ROC-analysis*. Waltham, MA: Academic Press.

Elberse, Anita (2008). Should you invest in the long tail?. *Harvard Business Review*, 86(7/8), 88–96.

Ellinger, Alexandeer E., Patricia J. Daugherty, and Craig M. Gustin (1997). The relationship between integrated logistics and customer service. *Transportation Research Part E: Logistics and Transportation Review*, 33(2), 129–138.

Ellinger, Alexandeer E., Patricia J. Daugherty, and Quentin J. Plair (1999). Customer satisfaction and loyalty in supply chain: The role of communication. *Transportation Research Part E: Logistics and Transportation Review*, 35(2), 121–134.

Fawcett, Tom (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, 27(8), 861–874.

Finney, David J. (1948). The Fisher-Yates Test of significance in 2x2 contingency tables. *Biometrika*, 35(1–2), 145–156.

Fornell, Claes (1992). A national customer satisfaction barometer: The Swedish experience. *Journal of Marketing*, 56(1), 6–21.

Gommans, Marcel, Krish S. Krishnan, and Katrin B. Scheffold (2001). From brand loyalty to e-loyalty: A conceptual framework. *Journal of Economic and Social Research*, 3(1), 43–58.

Granovetter, Mark S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6), 1360–1380.

Grewal, Dhruv, and Michael Levy (2009). Emerging issues in retailing research. *Journal of Retailing*, 85(4), 522–526.

Grewal, Dhruv, Jerry Gotlieb, and Howard Marmorstein (1994). The moderating effects of message framing and source credibility on the price-perceived risk relationship. *Journal of Consumer Research*, 21(1), 145–153.

Grewal, Dhruv, Julie Baker, Michael Levy, and Glenn B. Voss (2003). The effects of wait expectations and store atmosphere evaluations on patronage intentions in service-intensive retail stores. *Journal of Retailing*, 79(4), 259–268.

Grewal, Dhruv, and Michael Levy (2007). Retailing research: Past, present, and future. *Journal of Retailing*, 83(4), 447–464.

Grubb, Michael D. (2009). Selling to overconfident consumers. *The American Economic Review*, 99(5), 1770–1807.

Guillén, Montserrat, Jens Perch Nielsen, Thomas H. Scheike, and Ana Maria Pérez-Marín (2012). Time-varying effects in the analysis of customer loyalty: A case study in insurance. *Expert Systems with Applications*, 39(3), 3551–3558.

Gulati, Ranjay (1995). Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. *Academy of Management Journal*, 38(1), 85–112.

Guo, Chiquan (2001). A review on consumer external search: Amount and determinants. *Journal of Business and Psychology*, 15(3), 505–519.

Gurbaxani, Vijay, and Seungjin Whang (1991). The impact of information systems on organizations and markets. *Communications of the ACM*, 54(1), 59–73.

Harmon, Susan K., and C. Jeanne Hill (2003). Gender and coupon use. *Journal of Product and Brand Management*, 12(3), 166–179.

Hirshleifer, Jack (1965). Investment decisions under uncertainty: Choice theoretic approaches. *Quarterly Journal of Economics*, 79(4), 509–536.

Hitt, Lorin M., and Frances X. Frei (2002). Do better customers utilize electronic distribution channels? The case of PC banking. *Management Science*, 48(6), 732–748.

Homburg, Christian, Wayne D. Hoyer, and Martin Fassnacht (2002). Service orientation of a retailer's business strategy: Dimensions, antecedents, and performance outcomes. *Journal of Marketing*, 66(4), 86–101.

Jacoby, Jacob, and Robert W. Chestnut (1978). *Brand loyalty: Measurement and management*. New York: John Wiley & Sons.

Kahn, Barbara E. (1995). Consumer variety-seeking among goods and services: An integrative review. *Journal of Retailing and Consumer Services*, 2(3), 139–148.

Keh, Hean Tat, and Yih Hwai Lee (2006). Do reward programs build loyalty for services? The moderating effect of satisfaction on type and timing of rewards. *Journal of Retailing*, 82(2), 127–136.

Kivetz, Ran, and Itamar Simonson (2003). The idiosyncratic fit heuristic: Effort advantage as a determinant of consumer response to loyalty programs. *Journal of Marketing Research*, 40(4), 454–467.

Kumar, V., and Denish Shah (2004). Building and sustaining profitable customer loyalty for the 21st century. *Journal of Retailing*, 80(4), 317–329.

Laroche, Michel, Zhiyong Yang, Gordon H.G. McDougall, and Jasmin Bergeron (2005). Internet versus bricks-and-mortar retailers: An investigation into intangibility and its consequences. *Journal of Retailing*, 81(4), 251–267.

Lee, Ho G. (1998). Do electronic marketplaces lower the price of goods. *Communications of the ACM*, 41(1), 73–81.

Leenheer, Jorna, Harald J. van Heerde, Tammo H.A. Bijmolt, and Ale Smidts (2007). Do loyalty programs really enhance behavioral loyalty? An empirical analysis accounting for self-selecting members. *International Journal of Research in Marketing*, 24(1), 31–47.

Machina, Mark J. (2008). Expected utility hypothesis, in: Lawrence E. Blume, and Steven N. Durlauf (eds.), *The New Palgrave Dictionary of Economics.* Second Edition. Basingstoke: Palgrave Macmillan.

Malone, Thomas W., JoAnne Yates, and Robert I. Benjamin (1987). The logic of electronic markets. *Harvard Business Review*, 67(3), 166–172.

Mantel, Nathan (1963). Chi-square tests with one degree of freedom; Extensions of the Mantel-Haenszel procedure. *Journal of the American Statistical Association*, 58(303), 690–700.

McAlister, Leigh, and Edgar Pessemier (1982). Variety seeking behavior: An interdisciplinary review. *Journal of Consumer Research*, 9(3), 311–322.

Metz, Charles E. (1978). Basic principles of ROC analysis. *Seminars in Nuclear Medicine*, 8(4), 283–298.

Meyer-Waarden, Lars (2008). The influence of loyalty program membership on customer purchase behavior. *European Journal of Marketing*, 42(1–2), 87–114.

Mitchell, Vincent-Wayne, and Mike Greatorex (1993). Risk perception and reduction in the purchase of consumer services. *The Service Industries Journal*, 13(4), 179–200.

Mittal, Vikas, and Wagner A. Kamakura (2001). Satisfaction, repurchase intent, and repurchase behavior: Investigating the moderating effect of customer characteristics. *Journal of Marketing Research*, 38(1), 131–142.

Miyazaki, Anthony D., and Ana Fernandez (2001). Consumer perceptions of privacy and security risks for online shopping. *Journal of Consumer Affairs*, 35(1), 27–44.

Noble, Stephanie M., David A. Griffith, and Mavis T. Adjei (2006). Drivers of local merchant loyalty: Understanding the influence of gender and shopping motives. *Journal of Retailing*, 82(3), 177–188.

Oestreicher-Singer, Gal, and Arun Sundararajan (2010). Recommendation networks and the long tail of electronic commerce. *MIS Quarterly*, 36(1), 65–84.

Oliver, Richard L. (1997). *Satisfaction: A behavioral perspective on the consumer*. New York: McGraw-Hill.

Otnes, Cele, and Mary Ann McGrath (2001). Perceptions and realities of male shopping behavior. *Journal of Retailing*, 77(1), 111–137.

Pan, Yue, and Jason Q. Zhang (2011). Born unequal: A study of the helpfulness of user-generated product reviews. *Journal of Retailing*, 87(4), 598–612.

Peterson, Robert A., and Sridhar Balasubramanian (2002). Retailing in the 21st century: Reflections and prologue to research. *Journal of Retailing*, 78(1), 9–16.

Ramanathan, Ramakrishnan (2010). The moderating roles of risk and efficiency on the relationship between logistics performance and customer loyalty in e-commerce. *Transportation Research Part E: Logistics and Transportation Review*, 46(6), 950–962.

Ramsay, Barry (2010). E-loyalty: More of the same or something different. *Journal of International Academic Research*, 10(2), 1–18.

Ratner, Rebecca K., Barbara E. Kahn, and Daniel Kahneman (1999). Choosing less-preferred experiences for the sake of variety. *Journal of Consumer Research*, 26(1), 1–15.

Reichheld, Frederick F. (1993). Loyalty-based management. *Harvard Business Review*, 71(2), 64–73.

Reinartz, Werner, Manfred Krafft, and Wayne D. Hoyer (2004). The customer relationship management process: Its measurement and impact on performance. *Journal of Marketing Research*, 41(3), 293–305.

Ross, Ivan (1975). Perceived risk and consumer behavior: A critical review, in: Mary J. Schlinger (ed.), *Advances in Consumer Research.* Association for Consumer Research, 1–20.

Rubinstein, Ariel (1998). *Modeling Bounded Rationality*. Cambridge, MA: MIT Press.

Shankar, Venkatesh, Amy K. Smith, and Arvind Rangaswamy (2003). Customer satisfaction and loyalty in online and offline environments. *International Journal of Research in Marketing*, 20(2), 153–175.

Shapiro, Carl, and Hal R. Varian (1998). *Information rules: A strategic guide to the network economy*. Boston, MA: Harvard Business School Press.

Simon, Herbert A. (1957). *Models of man: social and rational; mathematical essays on rational human behavior in a social setting*. New York: Wiley.

Srinivasan, Srini S., Rolph Anderson, and Kishore Ponnavolu (2002). Customer loyalty in e-commerce: An exploration of its antecedents and consequences. *Journal of Retailing*, 78(1), 41–50.

Stanley, Thomas O., John K. Ford, and Sande K. Richards (1985). Segmentation of bank customers by age. *International Journal of Bank Marketing*, 3(3), 56–63.

Steven, Adams B., Yan Dong, and Martin Dresner (2012). Linkages between customer service, customer satisfaction and performance in the airline industry: Investigation of non-linearities and moderating effects. *Transportation Research Part E: Logistics and Transportation Review*, 48(4), 743–754.

Steyerberg, Ewout W., Andrew J. Vickers, Nancy R. Cook, Thomas Gerds, Mithat Gonen, Nancye Obuchowski, Michael J. Pencina, and Michael W. Kattan (2010). Assessing the performance of prediction models: A framework for traditional and novel measures. *Epidemiology*, 21(1), 128–138.

Tang, Esther P. Y., and Iris O. K. Chin (2007). Analyzing variety seeking behavior using panel data. *Journal of International Consumer Marketing*, 19(4), 7–31.

Tepper, Kelly Y. (1994). The role of labeling processes in elderly consumers' responses to age segmentation cues. *Journal of Consumer Research*, 20(4), 503–519.

Thakor, Mrugank V., Wendy Borsuk, and Maria Kalamas (2004). Hotlists and web browsing behavior – An empirical investigation. *Journal of Business Research*, 57(7), 776–786.

Tsai, Dungchun, and Hsiao-Ching Lee (2009). Demographics, psychographics, price searching and recall in retail shopping. *The Service Industries Journal*, 29(9), 1243–1259.

Uncles, Mark D., Grahame R. Dowling, and Kathy Hammond (2003). Customer loyalty and customer loyalty programs. *Journal of Consumer Marketing*, 20(4), 294–316.

Uzzi, Brian (1999). Social relations and networks in the making of financial capital. *American Sociological Review*, 64(4), 481–505.

Van Kenhove, Patrick, Kristof De Wulf, and Dirk Van den Poel (2003). Does attitudinal commitment to stores always lead to behavioral loyalty? The moderating effect of age. Ghent University: Working paper.

Vesel, Patrick, and Vesna Zabkar (2009). Managing customer loyalty through the mediating role of satisfaction in the DIY retail loyalty program. *Journal of Retailing and Consumer Services*, 16(5), 396–406.

Von Neumann, John, and Oskar Morgenstern (1944). *Theory of Games and Economic Behavior*. Princeton, NJ: Princeton University Press.

Wallace, David W., Joan L. Giese, and Jean L. Johnson (2004). Customer retailer loyalty in the context of multiple channel strategies. *Journal of Retailing*, 80(4), 249–263.

Walsh, Gianfranco, Thorsten Hennig-Thurau, Kai Sassenberg, and Daniel Bornemann (2010). Does relationship quality matter in e-services? A comparison of online and offline retailing. *Journal of Retailing and Consumer Services*, 17(2), 130–142.

Weathers, Danny, Subhash Sharma, and Stacy L. Wood (2007). Effects of online communication practices on consumer perceptions of performance uncertainty for search and experience goods. *Journal of Retailing*, 83(4), 393–401.

Wind, Jerry, and Arvind Rangaswamy (2001). Customerization: The next revolution in mass communication. *Journal of Interactive Marketing*, 15(1), 13–32.

Xevelonakis, Evangelos, and Patrick Som (2012). The impact of social network-based segmentation on customer loyalty in the telecommunication industry. *Journal of Database Marketing and Customer Strategy Management*, 19(2), 98–106.

Yoon, Sung-Joon (2002). The antecedents and consequences of trust in online-purchase decisions. *Journal of Interactive Marketing*, 16(2), 47–63.

Zeithaml, Valerie A., Leonard L. Berry, and A. Parasuraman (1996). The behavioral consequences of service quality. *Journal of Marketing*, 60(2), 31–46.

Zickuhr, Kathryn, and Aaron Smith (2012). *Digital differences*. Washington, D.C.: Pew Research Center.

II. COMPETING RISKS FOR TRAIN TICKETS – AN EMPIRICAL INVESTIGATION OF CUSTOMER BEHAVIOR AND PERFORMANCE IN THE RAILWAY INDUSTRY

"Not everything that counts can be counted, and not everything that can be counted counts."
Albert Einstein (1879-1955)

1. Abstract

Based on a comprehensive data set of German railway customers we analyze consumers' choices and particularly subsequent changes of two-part pricing contracts (loyalty cards). In a competing risks framework, we simultaneously estimate effects on three types of contractual events: cancellations, upgrades, and downgrades. Focusing on customer relationship management (CRM) practices, we find several factors affecting these events, some of which railway companies can influence to their advantage. Intuitively, installing auto-renewal procedures for loyalty cards decreases cancellation hazards. However, automated electronic mailings (e.g., reminders and account statements) and advertising (e.g., ticket offers) can be counterproductive and increase the risk of cancellation.

2. Introduction

Rail transportation has been the subject of increasing research in recent years because of its far-reaching economic, social, and environmental impacts at multiple societal levels. Numerous methodological and empirical studies have profoundly elaborated ways of handling railway timetabling, modeling and optimization of operations, as well as capacity and pricing issues (e.g., Abril et al. 2008; Batley, Dargay, and Wardma 2011; Corman et al. 2010, 2012; Hansen 2007; Lin et al. 2012). Another stream of research has focused on consumers' selection criteria and usage preferences for railway travel or other means of transport (e.g., Bhat and Sardesai 2006; Hess, Adler, and Polak 2007; Keumi and Murakami 2012).

However, in environments like the transportation and logistics sectors marked by increasing competition, researchers and practitioners alike have emphasized a growing need for customer orientation and relationship management (Ganesan et al. 2009). Reinartz, Krafft, and Hoyer (2004) define CRM at the customer-facing level as a systematic process to manage customer relationship initiation, maintenance, and termination across all customer contact points to maximize the value of the relationship portfolio. Boulding et al. (2005) explain that CRM relates to firm strategy and centers on the development of appropriate (long-term) relationships with specific customers or customer groups, the acquisition of customer knowledge, and the intelligent use of data and technology, to enhance customer loyalty and organizational performance.

Accordingly, interest in CRM practices in the transportation sector has grown considerably in recent years (see Daugherty et al. 2009; Ellinger, Daugherty, and Plair 1999; Grawe, Daugherty, and Dant 2012; Ramanathan 2010; Steven, Dong, and Dresdner 2012). However, research in the context of two-part pricing schemes is scarce. In addition, previous studies often neglect settings where travel decisions are not only based on consumers' current preferences, but are also influenced by previous contractual choices. As a consequence, a comprehensive approach towards understanding customers' travel behavior, and particularly, the determinants of their contractual choices and changes therein and how such decisions can be influenced effectively, is lacking in the literature on (rail) transportation settings.

In various international markets for rail transport, and particularly in the German market, severe oil price increases and growing environmental consciousness have helped public transit and rail transport to achieve substantial and profitable growth over the last decade. In 2011, the light rail traffic and the heavy rail sector served more than 2.5 billion railway travelers, most of them traveling by the major German railway company *Deutsche Bahn AG* (DB) (Statista 2011, p. 16). DB offers passengers the option of purchasing in advance various loyalty cards that act to discount ticket prices for 12 months from the date of issue. These contractual devices are commonly-known as BahnCards and are widely-used in German railway transportation.

Schmale, Ehrmann and Dilger (2013) have studied the travel behavior of German BahnCard customers and found that a disproportionately high proportion of customers fall victim to the 'flat rate bias' and underuse their BahnCards. Accordingly, based on the premise that customers strive to choose more suitable BahnCard contracts as time passes, in this study, we focus on analyzing the determinants (e.g., customer demographics, usage behavior, pricing, loyalty programs) of consumers' choices of BahnCard contracts as well as changes to these contractual choices over time. We collated comprehensive travel history data spanning a timeframe of almost six years and applied a non-generic competing risks framework. Using a semi-parametric proportional hazards model stratified by failure type, we simultaneously estimated effects on three types of contractual events: cancellation, upgrade, and downgrade of a BahnCard. In addition to identifying reasons for terminating a BahnCard or substituting a different one (which translates into an upgrade or a downgrade scenario), we were also able to quantify the magnitude of effects. We studied these issues based on a large-scale, longitudinal data set comprised of more than four million individual transactions. Accordingly, we find several factors affecting contract choices, some of which railway companies can influence to their advantage. Our study contributes to the literature by offering both theoretical and practical implications.

This paper proceeds as follows. In the next section, we describe the characteristics of the loyalty cards studied (here: BahnCards), and describe our data. The third section explains the methodology. We briefly introduce the concept of survival analysis, describe approaches towards competing risks and apply a specific method developed for the context at hand. We then report our main results; the last section offers a discussion and conclusions.

3. Characteristics of Loyalty Cards and the Study Data

Our analysis is based on proprietary customer data provided by DB. The data contain comprehensive information on customers' demographic characteristics, BahnCard contract choices, individual transaction data in the form of ticket purchase behavior over time, and fine-grained information on DB's CRM practices within its loyalty cards program. Based on these data we study the determining factors for consumers' choices of BahnCard contracts. The sample period is December 2002 through July 2008.

3.1 Contractual Options

DB customers can basically choose between three contracts: the BahnCard25 (BC25), the BahnCard50 (BC50) and the BahnCard100 (BC100). Each contract is available for first and second class travel. The number of the BahnCard contract type signifies the discount it affords on the regular ticket price for a 12 month period from the date of issue. Thus a BC25 gives a 25% discount, a BC50 means a 50% discount and a BC100 means a 100% reduction on standard domestic fares for a year. Currently, standard second class BahnCard contracts cost EUR 57 for the BC25, EUR 230 for the BC50 and EUR 3800 for the BC100. First class variants cost EUR 114 for the BC25, EUR 460 for the BC50 and EUR 6400 for the BC100. In addition to standard contracts, there are some exceptional price offers made in promotions and concessions for family members, students and senior citizens.

If they are not cancelled six weeks before the end date, BC25 and BC50 contracts are automatically renewed. The contract period for a BC100 is not renewed automatically. For BC25 and BC50 customers, it is always possible to upgrade within the contract period. Then, the residual value of the previous card is refunded. Customers may not downgrade contracts during their operative period.

3.2 Sample Construction and Key Variables

The data were drawn from the members of DB's customer loyalty programs "bahn.bonus" and "bahn.comfort" and include more than four million transactions conducted with any of the 800,000 BahnCards in the sample. Our data encompass the entire travel history of over 300,000 customers. Some adjustments were made to enhance reliability of the database. First, we excluded all loyalty program members whose overall lifetime sales did not exceed zero. Then, we dropped customers with inconsistent or not clearly assignable contracts (resulting from e.g., goodwill cancellations or registration errors). In addition, we concentrated on second class BahnCards to ensure contracts were comparable. Our final dataset features 200,851 BahnCards bought by 72,909 customers, with corresponding in-depth information on every single transaction conducted by those customers over time, including purchase dates, prices paid, reductions obtained, travel departure and destination, and number of passengers traveling. We focus on the history of BC25 and BC50 customers. (As BC100 users do not purchase any tickets due to their flat rate travel advantage, their travel behavior cannot be monitored). Our data also provides information about changes to different contracts, that is, an upgrade from a BC25 or from a BC50 to a 'higher' card, as well as downgrades following the expiry of a contract. We focus on the following variables:

begin and *end* (shows the validity period of each BahnCard), *cause* (represents the contract termination options, numbered 1 to 3; for BC25 customers: cancellation=1, upgrade to BC50=2, upgrade to BC100=3; for BC50 customers: cancellation=1, downgrade to BC25=2, upgrade to BC100=3), *sex* (female=0, male=1), *age* (measured in years, recorded at the time of purchase for each BahnCard), *auto-renewal* (defines the automatic renewal; default=1, if not terminated before the end of the cancellation period), *travel insurance* (indicates whether an insurance option has been used: no=0, yes=1), *email-flag* (marks a customer's agreement to receive automated electronic customer mailings: no=0, yes=1), *advertising ban* (stops any kind of (electronic) promotional mailings: no=0, yes=1), *comfort score* (displays the historic record of points in the bahn.comfort program that had already been collected by a customer at the start of the data collection period. "bahn.comfort" rewards customers who spend a certain sum on premium tickets with points that can then be spent on different products or services in return, e.g. other train tickets, first class upgrades or car rentals), *bonus score* (displays the score of points in the bahn.bonus program at the start of the data collection period. The bahn.bonus program awards points to customers based on the value of their ticket purchases; every euro spent on tickets yields one point in this program), *bonus account* (the overall bonus account in the corresponding customer lifecycle), *points redeemed* (the score of points previously exchanged for travel premiums), *higher status* (higher customer status in the bahn.bonus program: no=0, yes=1), *point of purchase* (purchase from a sales counter=0, purchase on the Internet=1), *BC price* (price of the particular BahnCard), *main card* (specifies whether the current BahnCard is a sole card or part of a group contract, e.g. for family members: no=0, yes=1), *business customer* (vs. private usage: no=0, yes=1); *quarter1*, …, *quarter4* (aggregated ticket fees per quarter, respectively); *number of budget prices* (number of tickets bought as special offers), *suboptimal* and *beyond optimal* (indicates the optimality of usage: no=0, yes=1; see the Appendix A for a detailed explanation of the parameters *suboptimal* and *beyond optimal*.), *comfort status* (specifies whether the BahnCard has comfort status concerning the bahn.comfort program: no=0, yes=1), *number of trips* (counts the quantity of tickets bought with each BahnCard) and finally, the number of tickets bought via five possible channels represented by: *# ticket machine*, *# ticket counter*, *# ticket internet*, *# ticket train conductor*, *# ticket call center* (indicating the number and source of the tickets bought by BahnCard).

3.3 Descriptive Statistics

In the sample, 44.8% of contracts with transactional data are BC25 contracts, 55.2% are BC50 contracts. Table 14 shows the descriptive statistics. On average, BC25 customers paid an initial fee of EUR 46.90, and BC50 customers paid EUR 137.81. The average BahnCard user spends the most on tickets in the first quarter of the validity period, whereas this amount continuously decreases in the following quarters for both regimes, BC25 and BC50. On average, total investments in tickets per BahnCard add up to EUR 99.61 for BC25 customers and EUR 221.38 for BC50 customers. Note that this usage behavior is beyond any rational optimality boundaries which should be a central driver of selecting a particular BahnCard (see also, Schmale, Ehrmann, and Dilger 2013; for a similar ‘flat rate bias’ concerning sports club memberships, see Della Vigna and Malmendier 2004, 2006).

The average BC25 customer buys 2.14 tickets per BahnCard, mostly from the counter, whereas a BC50 customer purchases an average of 6.96 tickets per BahnCard predominantly from the counter, as well as from ticket machines. Other purchasing options (the Internet, call centers, train conductors) are not widely adopted. Table 13 presents additional descriptive statistics on the customer level and reveals that the typical BC25 customer was around 43 years old, 58% of customers were female, and that they held 2.45 BahnCards during the sample period. A typical BC50 customer held 2.42 BahnCards over the period, is almost 42 years old, and 45% of them were men.

Customers	BC25		BC50	
Number of customers	31,780		41,129	
	Mean	Std. Dev.	Mean	Std. Dev.
Number of contracts	2.450811	1.477269	2.419579	1.365894
Sex (percentage male)	0.415739	0.4928517	0.4480613	0.4972973
Age	43.33092	17.35089	41.61757	19.82028

Table 13. *Descriptive Statistics: Customers*

Contracts	BC25		BC50	
Number of contracts	90,071		110,780	
	Mean	Std. Dev.	Mean	Std. Dev.
Auto-renewal	0.5841725	0.4928668	0.6120238	0.4872913
Travel insurance	0.1043399	0.3057027	0.125492	03312774
Email-flag	0.1339047	0.3405518	0.2133924	0.4097043
Advertising ban	0.0545402	0.2270818	0.0542036	0.2264201
Comfort score	142.7053	259.2779	312.802	470.5833
Bonus score	354.1909	525.4675	674.9599	868.4722
Bonus account	186.5099	270.1563	403.6948	489.7701
Points redeemed	7.768871	109.2736	37.42327	271.8575
Higher status	0.0037576	0.061184	0.0206322	0.1421504
Point of purchase	0.6797055	0.4665923	0.6373804	0.4807585
Price (initial fee)	46.89751	16.04926	137.8064	49.40856
Main card	0.8842136	0.3199704	0.9434104	0.2310579
Business customer	0.0057843	0.0758349	0.0190377	0.1366582
Total spending on tickets				
Quarter 1	31.23767	74.83283	71.6577	136.0392
Quarter 2	26.68095	68.11442	60.65741	119.524
Quarter 3	22.91953	63.0167	52.83188	110.8378
Quarter 4	18.77275	60.15871	36.23423	90.6738
Suboptimal	0.7409266	0.4381284	0.6084583	0.4880913
Number of budget prices	0.661856	1.958315	-	-
Beyond optimal	0.0699559	0.255074	0.003367	0.0579286
Comfort status	0.0069279	0.0829455	0.0337787	0.1806598
Number of trips	3.669538	7.926	9.585142	17.692
Number of tickets ordered via				
Ticket machine	0.4373328	2.520237	2.521294	7.786647
Ticket counter	1.490891	3.543353	3.836848	8.089226
Internet	0.0540018	0.526244	0.0198321	0.3152776
Train conductor	0.1107349	0.7818407	0.4452248	2.21877
Call center	0.0086709	0.1551538	0.0113739	0.2960557

Table 14. *Descriptive Statistics: Contracts*

4. Model

4.1 Background and Basic Hazard Model

Survival analysis has been a vital research objective in medical studies for several decades. Its techniques have, however, increasingly been adopted in social studies (Blossfeld, Hamerle, and Mayer 1986), technological fields, and (business) economics (Fan 2009; Iliescu, Garrow, and Parker 2008; Jain and Vilcassim 1991; Lee and Timmermans 2007; Light and Omori 2012; Sarstedt et al. 2010). What are termed *hazard models* are employed for the investigation of time duration until the occurrence of a specific event (see Cox 1972). The historical background of implementing survival time models explains the somewhat negative connotation of the event of interest, usually described as *failure (event)* or as *death*. In this paper, we are interested in analyzing changes in customer relationships. The point of time when a contract with a customer $i \in I$ changes is represented by a random variable with the density function $f(t_i)$ and a corresponding distribution function $F(t_i)$. For every particular time within the time interval T (*survival time*), the term $P(T \leq t_i)$ expresses the likelihood that there might be a change in the contract, in that, an event occurs. We can redefine:

$$F(t_i|\boldsymbol{X}_i) = P(T \leq t_i|\boldsymbol{X}_i) = \int_0^{t_i} f(\nu t_i|\boldsymbol{X}_i)/d\,\nu. \tag{1}$$

Its complement is given by the *survival function* that is defined as the probability by which customer i 'survives' time t_i: $S(t_i|\boldsymbol{X}_i) = P(T > t_i|\boldsymbol{X}_i) = 1 - F(t_i|\boldsymbol{X}_i)$. Now, it is possible to assess the risk for the occurrence of the event of interest at any specific time t_i for any customer i. Calculating this *failure rate* (also called *hazard rate*) results in the *hazard function*:

$$\lambda(t_i|\boldsymbol{X}_i) = lim_{\Delta t_i \to 0} \frac{P(t_i \leq T < t_i + \Delta t_i | T \geq t_i, \boldsymbol{X}_i)}{\Delta t_i}. \tag{2}$$

The hazard rate represents the instantaneous change rate for a customer relationship enduring up to time t_i and provides full characterization of the distribution of T (see Collett 2003). Hazard rate and survivor function are closely related, described by (see Allison 1995, p. 16):

$$\lambda(t_i|\boldsymbol{X}_i) = \frac{f(t_i|\boldsymbol{X}_i)}{S(t_i|\boldsymbol{X}_i)} \left(= \frac{f(t_i|\boldsymbol{X}_i)}{1 - F(t_i|\boldsymbol{X}_i)}\right). \tag{3}$$

In this context, the *cumulative hazard* is a commonly used term, which is defined by:

$$\Lambda(t) = \int_0^t \lambda(s) ds, \tag{4}$$

and accordingly applies to

$$S(t) = \exp(-\Lambda(t)). \tag{5}$$

The constitutive elements of hazard models are formed by the baseline hazard and the covariates. Semi-parametric approaches allow for the inclusion of covariates. The latter are parameterized in these models, but not the baseline hazard. This is particularly relevant when the key research study not only seeks to determine *whether* an event occurs, but also *on what* the occurrence of an event depends. A corresponding hazard regression model exhibits the form below (Cox 1972):

$$\lambda(t\,|\boldsymbol{X}) = \lambda_0(t) \cdot \exp(\boldsymbol{X\beta}), \tag{6}$$

where $\boldsymbol{X}$ consists of the customer-related measurements $\boldsymbol{X_i} = (X_{1i}, \dots, X_{pi})$ and $\boldsymbol{\beta}$ is a $p \times 1$ vector of unknown parameters. $\lambda_0(t)$ describes the baseline hazard that is an unknown function giving the hazard function for the standard set of conditions $\boldsymbol{X} = 0$. If the measured covariates of two individuals display identical values, the hazard functions will be the same. This model specifies distributions for the covariates without requiring any assumptions about the time-dependencies of the baseline hazards. It is also known as the *Cox (proportional hazards) model* (for a more detailed description, see Hosmer and Lemeshow 1999, p. 90 et seq.). The identical baseline hazard (for all individuals) and the time-independent covariates result in constant hazard ratios between individuals.

4.2 Competing Risks Framework

In our case, the subjects under investigation face three different scenarios at the end of the validity period of their respective contracts. This translates into a situation where a BahnCard contract is *at risk* of different types of mutually exclusive events (which are typically numbered from 1 to K) and constitutes a context of *competing risks*. Figure 7 illustrates this situation for

BC25 and BC50. The current BahnCard represents the initial state, that is, either a BC25 or a BC50 contract. In the first competing risks model, the endpoints "Cancellation", "Upgrade to BC50" or "Upgrade to BC100" are the three possible kinds of 'failure' for a BC25 customer. A BC50 contract is at risk of "Cancellation", "Downgrade to BC25" as well as "Upgrade to BC100", as modeled in the second competing risks framework.

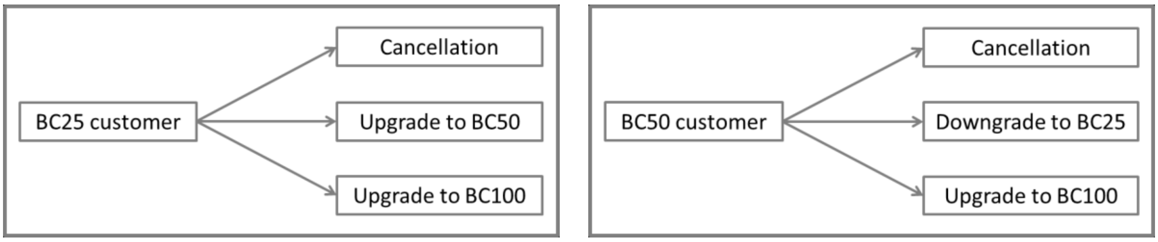


Figure 7. *Competing Risks Framework for the Two Regimes of our Sample*

With each BahnCard customer i we associate a pair (T, R), where T is the *time-to-event* (*survival* or *failure time*, as described above) and R refers to one of the kinds of failures for this customer, that is, the 'risk set'. The purpose of analyzing competing risks data can be interpreted to gain insights into the joint distribution of (T, R). In our model, each customer i is assumed to have an event time t_i and a censoring time c_i, meaning the end of our observations of i. Only the minimum of these failure times $x_i = \min(t_i, c_i)$ and its corresponding cause of failure are observed, whereas $\delta_i = I(t_i \leq c_i)$ indicates whether an event was observed at t_i (δ_i=1) or not (δ_i=0). For censoring caused by the end of the sample period, we assume that the censoring mechanism is independent of the distribution of contract changes (conditional on the covariates included in our model). Equally, the hazard to the customers who remain in the follow-up is assumed to be equal to the hazard of the censored customers (at each point in time). Given a certain time point, two different perspectives may be adopted when analyzing competing risks (Putter, Fiocco, and Geskus 2007; Vach 2005) and are explained below.

4.3 Models on Cause-Specific Hazards

One approach starts with the following questions: How does the risk of failure attributable to various causes change over time? What will happen around this particular time point when an event occurs? The probability to 'fail' from 'cause' k when a customer i has reached the time point t_i is in the focus of this perspective that leads to the so-called *cause-specific hazard functions.*

According to the conditions above, the *cause-specific hazard* function in the competing risk model is the hazard of failing from a given cause k in the presence of competing events:

$$\lambda_k(t) = lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t, R = k | T \geq t)}{\Delta t}, k = 1, \dots, K. \tag{7}$$

Allowing the baseline hazard to be different across subgroups (*strata*), the regression model on cause-specific hazards with cause k for a subject with covariates $\boldsymbol{X}$ is given by:

$$\lambda_k(t|\boldsymbol{X}) = \lambda_{k,0}(t) \exp(\boldsymbol{\beta}_k^T \boldsymbol{X}) . \tag{8}$$

Another perspective on cause-specific hazards considers how many customers changed their contract (at its end) in a specific way and what had happened up until that point in time. Therefore, we consider the probability of failure from cause k up to this point, which is reflected in the (*cause-specific*) *cumulative incidence function* (CIF). For this purpose, we define the cumulative cause-specific hazard by

$$\Lambda_k(t) = \int_0^t \lambda_k(s) ds, \tag{9}$$

and accordingly, as in the intercept, above

$$S_k(t) = \exp(-\Lambda_k(t)). \tag{10}$$

Note that this term can be interpreted as the marginal survival function, that is, the survival probability for the k^{th} risk, only if competing event time distributions and censoring time distribution are independent. This describes a situation where all other risks have been hypothetically removed (see Putter, Fiocco, and Geskus 2007). In addition, we propose

$$S(t) = \exp(-\sum_{k=1}^K \Lambda_k(t)) \tag{11}$$

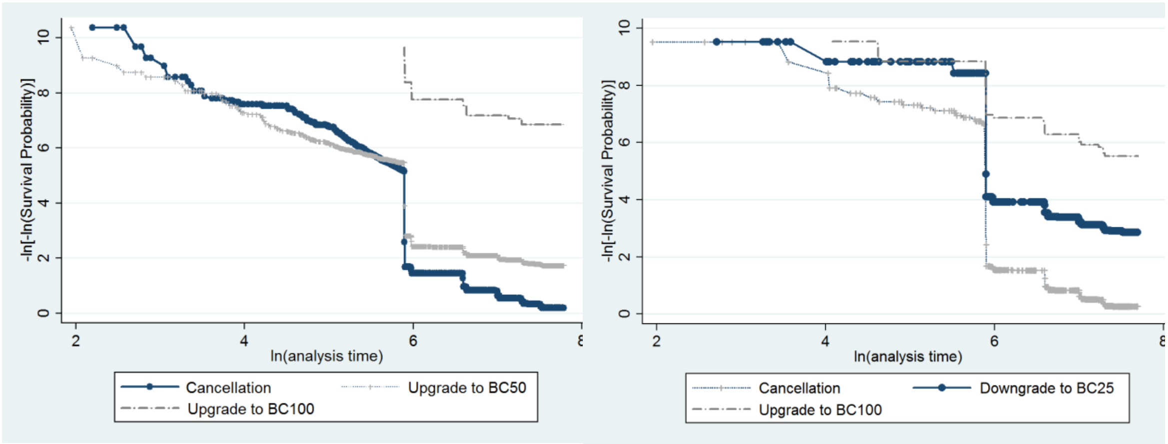
to model the probability of not having experienced any events before time t. The CIF is then given by:

$$I_k(t) = P(T \leq t, R = k) = \int_0^t \lambda_k(s) S(s)\, ds, k = 1, \dots, K. \quad (12)$$

The latter expression obviously indicates that the cumulative incidence of a specific cause k is a function of both the probability of not having experienced the event up to time $t(S(s))$ and the cause-specific hazard at this time $\lambda_k(s)$ (see also, Kalbfleisch and Prentice 2002).

Lunn and McNeil (1995) provide methods for a joint estimation of parameters in models for competing risks by fitting a Cox proportional hazard model via a duplication method. We applied their first approach (Method A) and introduced two variables: a failure type indicator (*cause*) and a *status* parameter which is a numeric representation of the competing risk variable *cause*, indicating whether the corresponding event occurs (*status*=1) or not (*status*=0). Any covariates are then replicated according to the total number K of events, whereas the time variables *begin* and *end* are identical over the K replications. In our case, the three different causes, or types of events, translated into a triplication of the data. Then, the hazards of all causes were assumed to be additive, so the total hazard equals the value of the sum of its corresponding hazard functions. Thus, the hazard of failure is the sum of K component risk processes, and the failure time of either type is considered the minimum of these (Lunn and McNeil 1995). Apart from the aspect of flexibility (the stratified method permits distinct baseline hazards for each event type, see also, Jeong and Fine 2007), the alternative approach (Method B) by Lunn and McNeil (1995) requires a constant ratio of the baseline hazard functions. However, Grambsch and Therneau's (1994) test of the proportional hazards assumption based on Schoenfeld residuals reveals that this assumption does not hold for most of the variables (of either population). Additionally, the global test is highly significant for both customer groups (p < 0.001). The same result can be traced in Figure 8, which shows plots of $-\ln\left(-ln\left(S(t)\right)\right)$ against $\ln(t)$: the absence of adequate parallelism between the graphical representation of the three failure types justifies the stratified version of the approach by Lunn and McNeil (1995) (Method B). Hence, we employed a semi-parametric proportional hazards model (see (9)) stratified by failure type.

This is done by comparing the covariate values of customers when they move to state k with the covariates of those customers still event-free and in the follow-up. Customers who move to another state are censored at the point of their transition.



BC25 population BC50 population

Figure 8. *Relationship of the Baseline Hazard Functions between Different Failure Types*

The advantage of this approach is its ability to simultaneously fit cause-specific hazard models for all causes, and to investigate the equality of the effects of covariates on different causes of failure, that is, changes of BahnCard contracts (see also, Andersen and Borgan 1985; Lunn and McNeil 1995; Putter, Fiocco, and Geskus 2007).

4.4 Models on Subdistribution Hazards

Another approach to analyzing competing risks data is based on the ideas of Fine and Gray (1999). They propose a semi-parametric regression model for the subdistribution of a competing risk that aims to establish direct effects of covariates on the cumulative incidence probabilities, which essentially helps avoid highly nonlinear effects of covariates on the CIFs when modeling is done on cause-specific hazards (Putter, Fiocco, and Geskus 2007). Fine and Gray (1999) define a *subdistribution hazard* so that the covariate effect directly relates to the CIF:

$$\lambda_k^*(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t, R = k | T \geq t \cup (T < t \cap R \neq k))}{\Delta t} = -\frac{d \log(1 - I_k(t))}{dt}. \quad (13)$$

Thus, the CIF for cause k depends on the hazard of cause k as well as on the hazards of all other possible causes. Contrary to the cause-specific hazards, every customer who experienced an event from another cause remains in the risk set, whereas for the cause-specific hazard, the risk set decreases with every event. Similarly to the regression model on cause-specific hazards represented by equation 9 above , this can be expressed by following regression model:

$$\lambda_k^*(t|\boldsymbol{X}) = \lambda_{k,0}^*(t)\exp\left(\boldsymbol{\beta}_k^T\boldsymbol{X}\right). \tag{14}$$

Cause-specific hazards as well as subdistribution hazards, i.e. the cumulative incidence as a function of the cause-specific hazard, can be predicted from the data. With the latter method all possible events are taken into account and the censoring mechanism is assumed to be independent of the change progression of BahnCard contracts. We complement our analysis by graphical evaluations based on Fine and Grey's (1999) approach using the subdistribution hazards. It may be added that these competing risks models do not allow investigation of potential associations between causes. Therefore, the interpretation of results requires a combined view of data insights and theoretically based, logical reasoning. Concerned with the question of which factors determine consumers' changed contractual choices, and to suggest how their decisions could be influenced effectively by the firm, we also strive to quantify each factor's effects in the competing risks framework.

5. Results

The empirical results of our competing risks models for BC25 customers are presented in Table 15. The corresponding results for BC50 customers are displayed in Table 16. Hazard ratios are a measure of relative risks over time, and results higher than 1 indicate a higher probability of the corresponding event caused by the relevant covariate (accordingly, a result of less than 1 indicates a lower risk). Table 17 outlines the goodness-of-fit for the different model scenarios illustrated above (see Figure 7) according to O'Quigley, Xu, and Stare (2005) who propose a modified version of the Nagelkerke R^2 in which the number of observations is replaced by the number of uncensored observations (events).

To ascertain appropriate model fit, we employed Cox-Snell residuals and show that these residuals have an approximate standard censored exponential distribution with hazard ratio 1 (Blossfeld, Golsch, and Rohwer 2007, p. 219 et seq.). Based on the Kaplan and Meier (1958) estimated survivor function, we calculate an empirical estimate of the cumulative hazard function, using the Cox-Snell residuals as the time variable and the data's original censoring variable. If the model fits the data, the plot of the cumulative hazard versus the Cox-Snell residuals results in an approximation of a straight line of slope 1. The results of these graphical validations of our model are displayed in Figure 9. In the following section, we focus on presenting the most significant results.

		Event	Hazard Ratio	95% Conf. Interval		P>|z|
Sex						
		Cancellation	.9831377	.9521172	1.015169	0.299
	Influence on event	Upgrade to BC50 *	.9158966	.8512729	.9854262	0.019
		Upgrade to BC100	1.53856	.4753589	4.979749	0.472
Age						
		Cancellation ***	.9880395	.986978	.9891021	0.000
	Influence on event	Upgrade to BC50 *	.9970026	.9945128	.9994986	0.019
		Upgrade to BC100 *	.9700497	.9415085	.9994561	0.046
Auto-renewal						
		Cancellation ***	.1005775	.0956211	.1057907	0.000
	Influence on event	Upgrade to BC50 ***	.1671777	.1533873	.182208	0.000
		Upgrade to BC100	.4418717	.1022061	1.910361	0.274
Travel insurance						
		Cancellation *	.9416153	.8964317	.9890764	0.016
	Influence on event	Upgrade to BC50	1.050223	.9329413	1.182249	0.417
		Upgrade to BC100	.1520467	.0049468	4.673409	0.281
Email-flag						
		Cancellation ***	1.404874	1.251889	1.576554	0.000
	Influence on event	Upgrade to BC50 ***	1.233397	1.101353	1.381272	0.000
		Upgrade to BC100	.1970921	.0269256	1.442689	0.110
Advertising ban						
		Cancellation	.9480582	.868083	1.035401	0.236
	Influence on event	Upgrade to BC50 ***	1.69879	1.486557	1.941324	0.000
		Upgrade to BC100	0	.		.
Comfort score						
		Cancellation ***	.9944637	.994008	.9949197	0.000
	Influence on event	Upgrade to BC50 ***	1.001387	1.001209	1.001564	0.000
		Upgrade to BC100	1.00131	1.00069	1.00193	0.000
Bonus score						
		Cancellation ***	.9982089	.9980081	.9984098	0.000
	Influence on event	Upgrade to BC50 ***	1.000297	1.000196	1.000397	0.000
		Upgrade to BC100 **	1.000239	.9997356	1.000742	0.352
Bonus account						
		Cancellation ***	1.001532	1.001162	1.001903	0.000
	Influence on event	Upgrade to BC50 *	.9996683	.9993716	.999965	0.028
		Upgrade to BC100 *	.9973597	.9947434	.9999828	0.049
Points redeemed						
		Cancellation	1.00019	.9998186	1.000561	0.316
	Influence on event	Upgrade to BC50	.9998613	.9995455	1.000177	0.390
		Upgrade to BC100	1.113334	.		.
Higher status						
		Cancellation ***	4.268563	1.841921	9.892191	0.001
	Influence on event	Upgrade to BC50 ***	.0427814	.0235811	.0776151	0.000
		Upgrade to BC100	4.07073	.0923593	179.4171	0.467
Point of purchase						
		Cancellation ***	.4021331	.3775837	.4282786	0.000
	Influence on event	Upgrade to BC50 ***	.3745662	.3294605	.4258473	0.000
		Upgrade to BC100	.5227959	.1351563	2.022218	0.347
BC price						
		Cancellation ***	.9739082	.9714177	.9764052	0.000
	Influence on event	Upgrade to BC50 †	1.050394	1.028074	1.073199	0.000
		Upgrade to BC100	1.099604	.8807148	1.372896	0.402
Main card						
		Cancellation ***	4.305562	3.782397	4.901088	0.000
	Influence on event	Upgrade to BC50	.0839336	.0287988	.2446235	0.000
		Upgrade to BC100	.0161338	9.00e-07	289.0938	0.409
Business customer						
		Cancellation	1.072379	.895533	1.284147	0.447
	Influence on event	Upgrade to BC50 *	1.351647	1.011831	1.805589	0.041
		Upgrade to BC100	0	.		.
Quarter 1						
		Cancellation ***	.9989969	.9984495	.9995446	0.000
	Influence on event	Upgrade to BC50	1.000511	.9998375	1.001185	0.137
		Upgrade to BC100	1.001401	.9917035	1.011193	0.778
Quarter 2						
		Cancellation ***	.9988826	.9983182	.9994473	0.000
	Influence on event	Upgrade to BC50	1.000298	.9996668	1.000929	0.355
		Upgrade to BC100 †	1.008613	1.002591	1.014671	0.005
Quarter 3						
		Cancellation ***	.9988446	.998241	.9994486	0.000
	Influence on event	Upgrade to BC50 †	1.000338	.9996567	1.001021	0.331
		Upgrade to BC100	.997232	.9876978	1.006858	0.572

Quarter 4 [Continued]

Quarter 4				
Influence on event	Cancellation ***	.9976247	.996959 .9982907	0.000
	Upgrade to BC50 †	1.000479	.9999132 1.001045	0.097
	Upgrade to BC100	1.001804	.9953191 1.008331	0.586
Number of budget prices				
Influence on event	Cancellation *	.9809367	.9661835 .9959152	0.013
	Upgrade to BC50 ***	.9400421	.9129409 .9679479	0.000
	Upgrade to BC100	1.480314	.8871466 2.470088	0.133
Suboptimal				
Influence on event	Cancellation *	.9317008	.8820177 .9841825	0.011
	Upgrade to BC50	1.076839	.9682574 1.197596	0.172
	Upgrade to BC100	.5602439	.2782977 1.127833	0.105
Beyond optimal				
Influence on event	Cancellation †	1.110313	.9937514 1.240548	0.064
	Upgrade to BC50	.8750105	.723879 1.057695	0.168
	Upgrade to BC100	.135992	.0109309 1.691883	0.121
Comfort status				
Influence on event	Cancellation †	.7186443	.5052614 1.022143	0.066
	Upgrade to BC50 ***	2.289067	1.768406 2.963024	0.000
	Upgrade to BC100 ***	82.24907	7.696763 878.9291	0.000
Number of trips				
Influence on event	Cancellation	1.005963	.9964567 1.015561	0.220
	Upgrade to BC50 ***	.9708735	.955802 .9861827	0.000
	Upgrade to BC100 *	.6520072	.4649859 .91425	0.013

Ticket device variables (ticket machine, counter, Internet, train conductor, call center) are included in the regressions, yet they are of minor importance. For readability, results are omitted from the tables but can be obtained upon request.

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 15. *Estimation Results for the BC25 Customers*

		Hazard Ratio	95% Conf. Interval	P>|z|
Sex				
Influence on event	Cancellation	1.019445	.9930353 1.046557	0.150
	Downgrade to BC25 ***	.7543554	.6686753 .851014	0.000
	Upgrade to BC100	.8544644	.4997539 1.460938	0.565
Age				
Influence on event	Cancellation ***	.9888792	.9880751 .989684	0.000
	Downgrade to BC25 ***	1.006655	1.003394 1.009926	0.000
	Upgrade to BC100 ***	.9456529	.9218819 .9700367	0.000
Auto-renewal				
Influence on event	Cancellation ***	.0802754	.0763434 .08441	0.000
	Downgrade to BC25 ***	.1012532	.0865317 .1184793	0.000
	Upgrade to BC100 ***	.0703011	.0341526 .1447108	0.000
Travel insurance				
Influence on event	Cancellation	1.012378	.9740886 1.052172	0.532
	Downgrade to BC25	.8989318	.7489946 1.078884	0.252
	Upgrade to BC100	1.21479	.5909328 2.497264	0.597
Email-flag				
Influence on event	Cancellation ***	1.194953	1.125873 1.268272	0.000
	Downgrade to BC25 ***	1.437945	1.194849 1.7305	0.000
	Upgrade to BC100	.7423887	.4585261 1.201984	0.226
Advertising ban				
Influence on event	Cancellation *	.9058221	.8338909 .9839581	0.019
	Downgrade to BC25 ***	1.514794	1.195787 1.918905	0.001
	Upgrade to BC100	1.078664	.3880323 2.998502	0.885
Comfort score				
Influence on event	Cancellation ***	.9948439	.9945933 .9950946	0.000
	Downgrade to BC25 *	.9995745	.9993051 .9998439	0.002
	Upgrade to BC100 ***	1.000663	1.000384 1.000941	0.000
Bonus score				
Influence on event	Cancellation ***	.999469	.9993988 .9995393	0.000
	Downgrade to BC25	.9999417	.9997861 1.000097	0.462
	Upgrade to BC100 **	.9999827	.9998208 1.000145	0.834
Bonus account				
Influence on event	Cancellation ***	1.000875	1.000748 1.001003	0.000
	Downgrade to BC25	.9998358	.9993258 1.000346	0.528
	Upgrade to BC100	.9997125	.9993314 1.000094	0.139
Points redeemed				
Influence on event	Cancellation	.9999654	.9998759 1.000055	0.449
	Downgrade to BC25	1.000045	.9997815 1.000308	0.740
	Upgrade to BC100 †	1.000377	.999978 1.000777	0.064

[Continued]

Higher status					
	Cancellation ***	1.940388	1.347588	2.793959	0.000
Influence on event	Downgrade to BC25	.7907622	.3829959	1.632667	0.526
	Upgrade to BC100 ***	917.0298	154.6894	5436.336	0.000
Point of purchase					
	Cancellation ***	.7075465	.6724928	.7444274	0.000
Influence on event	Downgrade to BC25 **	.7309667	.5783598	.9238408	0.009
	Upgrade to BC100	.8908078	.4442946	1.786064	0.745
BC price					
	Cancellation ***	1.001705	1.0014	1.00201	0.000
Influence on event	Downgrade to BC25 †	1.005927	1.004645	1.007211	0.000
	Upgrade to BC100	1.00141	.9956273	1.007226	0.633
Main card					
	Cancellation	1.039908	.9742235	1.110022	0.240
Influence on event	Downgrade to BC25 ***	.5991031	.4828535	.7433406	0.000
	Upgrade to BC100	.9643917	.2105621	4.416992	0.963
Business customer					
	Cancellation ***	1.227075	1.111289	1.354924	0.000
Influence on event	Downgrade to BC25 ***	.2748114	.1464893	.5155413	0.000
	Upgrade to BC100	.9863642	.3320596	2.929939	0.980
Quarter 1					
	Cancellation ***	.9996295	.9994016	.9998575	0.001
Influence on event	Downgrade to BC25 *	.9986077	.9976208	.9995957	0.006
	Upgrade to BC100	.9996038	.9981728	1.001037	0.588
Quarter 2					
	Cancellation ***	.9992629	.999012	.999514	0.000
Influence on event	Downgrade to BC25 †	1.000986	.9999708	1.002002	0.057
	Upgrade to BC100 †	1.000079	.998072	1.002091	0.938
Quarter 3					
	Cancellation ***	.9992312	.9989291	.9995335	0.000
Influence on event	Downgrade to BC25 †	1.000271	.9992739	1.00127	0.594
	Upgrade to BC100 †	.9981224	.996014	1.000235	0.082
Quarter 4					
	Cancellation ***	.9985786	.9982318	.9989254	0.000
Influence on event	Downgrade to BC25 *	1.000944	1.000089	1.0018	0.030
	Upgrade to BC100 *	.9981153	.9964004	.9998331	0.032
Number of budget prices	*Note that a BC50 cannot be combined with any discounts.*				
Suboptimal					
	Cancellation ***	.8733237	.836787	.9114558	0.000
Influence on event	Downgrade to BC25	1.047645	.8781074	1.249916	0.605
	Upgrade to BC100 †	1.037439	.4701544	2.289206	0.927
Beyond optimal					
	Cancellation	1.196737	.5288381	2.708161	0.666
Influence on event	Downgrade to BC25	.7676126	.1344961	4.381014	0.766
	Upgrade to BC100 *	.7648551	.1611634	3.629877	0.736
Comfort status					
	Cancellation ***	.8179429	.728032	.9189577	0.001
Influence on event	Downgrade to BC25 **	1.772347	1.204349	2.608224	0.004
	Upgrade to BC100 *	2.03037	1.089155	3.784954	0.026
Number of trips					
	Cancellation	.9990129	.9954039	1.002635	0.593
Influence on event	Downgrade to BC25 †	1.00799	.9989977	1.017063	0.082
	Upgrade to BC100	1.005172	.9961178	1.014308	0.264

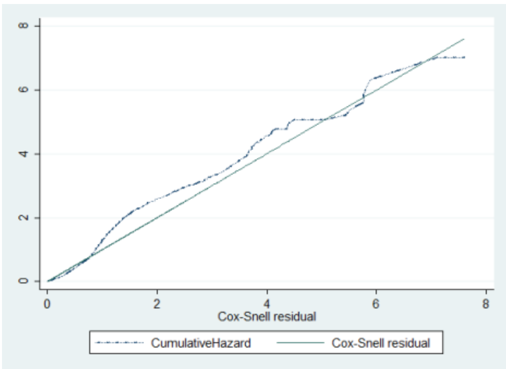
Ticket device variables (ticket machine, counter, Internet, train conductor, call center) are included in the regressions, yet they are of minor importance. For readability, results are omitted from the tables but can be obtained upon request.

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

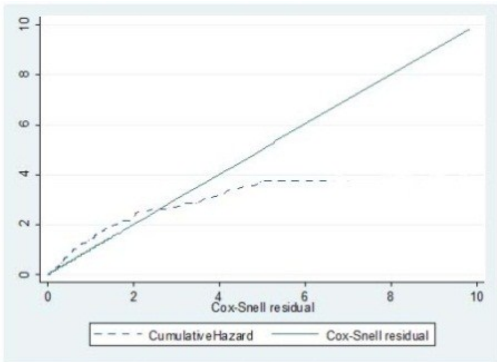
Table 16. *Estimation Results for the BC50 Customers*

	Scenario	No. Events	Adj. R^2	Boot. SE	95% conf.	interval
BahnCard25						
	Cancellation	12099	0.753757	0.004215	0.745860	0.762878
	Upgrade BC50	3003	0.609709	0.012973	0.588089	0.639157
	Upgrade BC100	71	0.797490	0.003787	0.790461	0.806983
BahnCard50						
	Cancellation	15290	0.821689	0.002791	0.816400	0.827487
	Downgrade BC25	1188	0.586956	0.020110	0.555061	0.633349
	Upgrade BC100	264	0.788934	0.003991	0.780065	0.798986

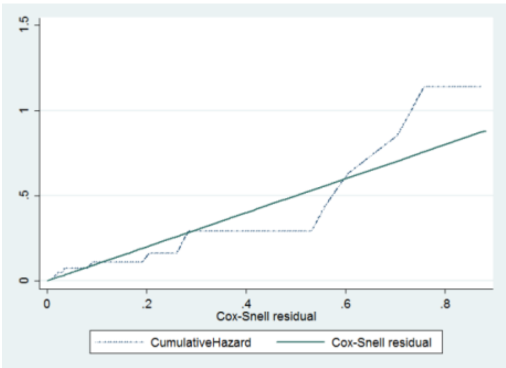
Table 17. *Goodness-of-Fit of the Employed Model Framework*



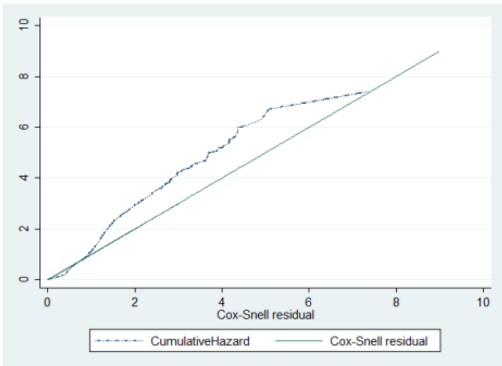
Cancellation of BC25



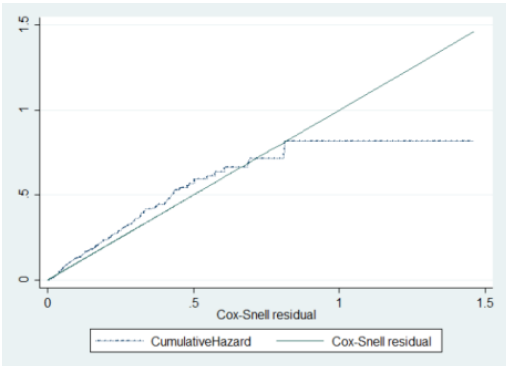
Upgrade to BC50



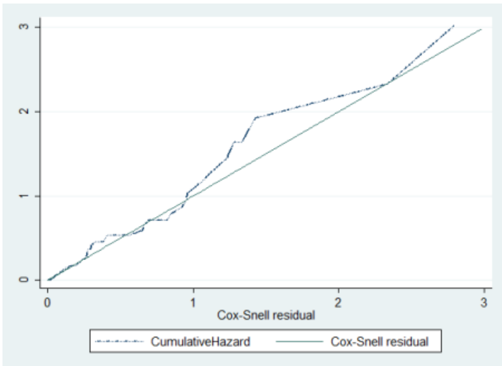
BC25: Upgrade to BC100



Cancellation of BC50



Downgrade to BC25



BC50: Upgrade to BC100

Figure 9. *BC25-Model-Fit and the BC50-Model-Fit based on Cox-Snell Residuals*

Demographics.

As regards demographics, gender has a relatively small influence on changes in BC contracts. However, concerning the choice of downgrading a BC50 to a BC25, we observe that men are nearly 25% less likely to downgrade a BC50 than women. Given that most BahnCard owners underuse their cards, men seem to have even less ability to recognize inappropriate contract choices or to take appropriate action than women (which might indicate that men are even more susceptible to status quo bias and loss aversion than women).

Age is a very significant factor, but the strength of its influence is rather small. Older people, possibly due to more conservative decision-making, cancel less often and are reluctant to upgrade a BC25 to a BC50, yet they are more likely to downgrade a BC50 to a BC25.

CRM practices.

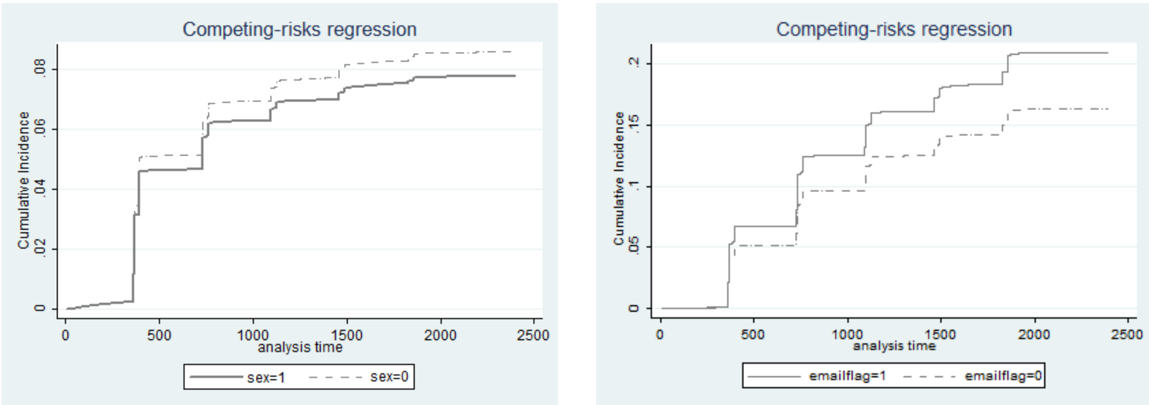
Turning to DB's practices that may help develop and maintain customer relationships within the BahnCard framework, *auto-renewal* greatly reduces cancellation risk (by around 90% for both BC25 and BC50). Although auto-renewal as the default option upon contract expiry seems intuitively beneficial for the firm, it is detrimental to upgrades. The probability of a customer upgrading decreases by 83% for BC25 holder and by 93% for a BC50 holder. On the other hand it does at least reduce the risk of a customer downgrading from a BC50 considerably (by 90%). To summarize, auto-renewal is a most effective way to bind in BahnCard owners.

Interestingly, the *email-flag*, indicating that a customer agreed to receive automated mailings from DB, increases the cancellation hazards of both BC25 (40%) and BC50 (20%) cards. It also enhances BC25 upgrade (23%) and downgrade (44%) hazards (Figure 11 and 12). Thus, automated mailings may be difficult to implement in a way that predictably affects firm performance. Similarly, *advertising bans*, indicating that customers rejected electronic advertising being sent to their mail accounts, lower the cancellation rate of BC50 customers by 9%. Yet, their downgrading risk rises by 51%. Nevertheless, the upgrading of a BC25 becomes 70% more probable.

Hence, there might be a need to re-develop and fine-tune CRM practices as regards email policies. Customers who do not object to receiving emails are more likely to cancel and downgrade their BahnCards, yet this factor simultaneously fosters opportunities for BC25 upgrades. Similarly, reducing electronic advertising activity to BC25 customers should not only save money, but also facilitate retaining customers and enhance the probability of a BC25 upgrade. Yet, an advertising ban significantly increases the risk of downgrading a BC50. A more detailed examination and maintained monitoring of not only *how*, but particularly *whom* to address (via *which* channels), seems advisable to exploit the potential and increase the effectiveness of electronic customer contact initiated by the firm.

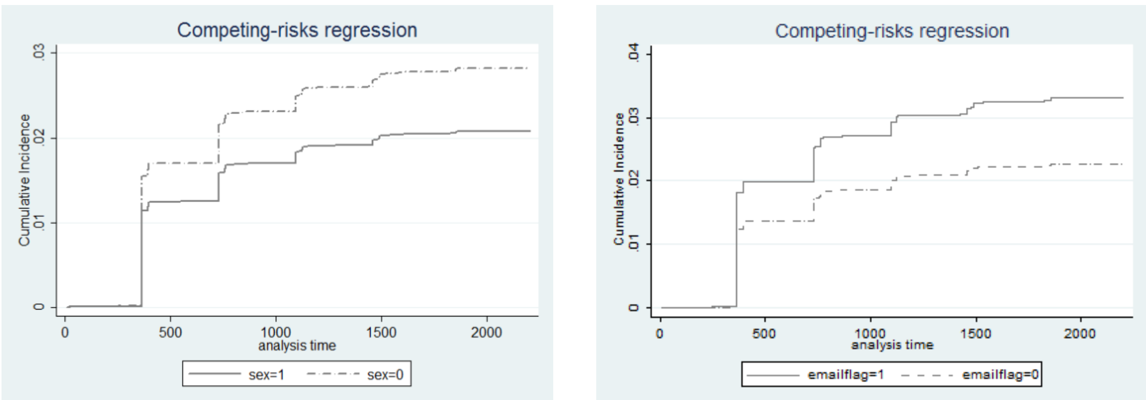
With respect to distribution strategies for BahnCards, another interesting result is that the *point of purchase* seems to affect stability in DB customer contracts in comparison to purchase over the counter as a reference point. Internet purchase reduces cancellation, upgrade and downgrade risks (in the case of BC25 by about 60% in each case, and for BC50 by about 30%). This finding raises the question of how different consumer segments might be directed to 'more promising' points of sale to enhance customer retention and upgrading activity, and how purchases via the Internet could be promoted in future.

Concerning the customer loyalty programs, we observed some counterintuitive results as well. *Bonus score* and *comfort score* are significant in most scenarios. Surprisingly, a score increase slightly raises the cancellation hazard for both BC25 and BC50 cards. Point redemption is not significant in any of the scenarios and subgroups (Table 13 also documents that many DB customers never redeem their points). However, the amenities offered by *comfort status* proved a very useful 'reward' for BahnCard owners since they strongly escalated upgrade hazards and decreased cancellation risks. Yet, for BC25 customers, becoming a *status customer* enhances the cancellation hazard by a factor of four and lowers the probability of upgrading by 95%. Thus, offering a bahn.bonus program in the BC25 customer segment seems very disadvantageous; although it is advantageous in the BC50 segment, where it is (despite, unfortunately, doubling the cancellation hazard) a highly relevant indicator for BC100 upgrades. Accordingly, a central question is why customers who have acquired a higher status in the loyalty program, and are therefore frequent travelers, are more likely to abandon their relationship with DB. Potential explanations might include that this reaction is either caused by an increase in DB's automated customer mailings, which repel customers, or by temporal effects; perhaps even long-standing customers cancel their contract at some time (on average, after 2.5 contracts). In addition, the more a customer travels, the more familiar they will become with pricing schemes and alternative ways of obtaining price reductions (e.g., early bird offers, special promotions), so that the perceived advantage of holding a BahnCard may decrease with increasing knowledge about the company's pricing strategy (this may also explain that with an increase in collected loyalty scores, derived from high travel frequency, cancellation hazards of both BC25 and BC50 customers rise). In conclusion, it seems reasonable to adjust the loyalty program particularly to increase retention rates for the BC25 customer segment and redesign pricing strategies in a way that emphasizes the BC advantages.



Event type: upgrade to BC50 Event type: cancellation

Figure 10. *Cumulative Incidence (BC25) with Respect to Sex and Email-Flag*



Event type: downgrade to BC25 Event type: cancellation

Figure 11. *Cumulative Incidence (BC50) with Respect to Sex and Email-Flag*

Pricing and usage.

Concerning changes in the *price* of a BahnCard, all hazards appear more pronounced for the BC25 population. A higher *price* for the original BC25 reduces the cancellation risk, which could be triggered by the fact that BahnCards bought for a lower price during promotional campaigns by DB are less likely to be renewed. The cancellation risk of a BC50 hardly changes with increasing BahnCard prices. *Business customers* with a BC50 are 23% more likely to cancel their cards, but 73% less likely to downgrade than private users. Furthermore, a BC25 business customer is 35% more likely to upgrade to a BC50 than a private user. The total sum of ticket fees per *quarter* reduces the probability of cancellation in all quarters for both types of cards. Higher fees (significant only in the third and fourth quarter) tend to increase the probability of upgrading from a BC25 to a BC50.

Contrary to expectations, a *suboptimal* use of a BahnCard in terms of its 'under-usage' reduces the cancellation hazards for both BC25 and BC50 segments. For customers whose travel behavior is *beyond* the optimality boundaries ('over-usage'), the risk of cancellation rises. Moreover, the *number of trips* turns out to be of moderate importance in explaining the competing risks in the context of BahnCard contracts. Each additional trip by rail decreases the upgrade probabilities from a BC25 to a BC50 by 3% and to a BC100 by 35%. Besides, a BC25, but not a BC50, can be used in combination with otherwise (other than BC-related) reduced tickets ('budget prices'). Here, each ticket combined with an additional discount reduces the cancellation hazard by 2% and the upgrade hazard to a BC50 by 6%. In addition, we studied the devices used to buy a ticket. Ticket device variables have a slight effect on contractual changes but, particularly for cancellation events, they are of minor importance.

Finally, another interesting finding is that competing risks models based on subdistribution hazards illustrate that cancellation as well as upgrade and downgrade proportions are influenced by the time passed since the (initial) BahnCard purchase. Accordingly, our results support observations made by Iliescu, Garrow, and Parker (2008) in the airline industry, who found that higher cancellation rates are often observed for recently purchased tickets. Our results document that change rates of all types of events in our study (and especially cancellation rates) decrease with a growing number of contract extensions (Figure 10 and 11).

6. Discussion and Conclusion

This study demonstrates how hazard models combined with data multiplication methods can be used in a context of competing risks to model railway travelers' choices of two-part pricing contracts in terms of contract cancellation, upgrade and downgrade behavior. Specifically, we estimate an 'initial-change' model for annual train ticket contracts (BahnCards) based on the occurrence of cancellation events or loyalty card changes in a large-scale sample from *Deutsche Bahn AG*. In comparison to other models of this type described in the literature or used in practice, the proposed model takes a customer-centric approach, as it captures the underlying behavior of train passengers. We extend the conventional cancellation risks framework by applying competing risks models to the specific context of customer loyalty cards, which provides a broader perspective on customer retention in the railway sector. Our method originates from survival analysis and has not been transferred to transportation studies on consumer travel behavior before. The model is appropriate to examine consumers' contractual choices across different segments of the population (male vs. female, young vs. old, business customers vs. consumers etc.) and across varying usage intensities (low, medium, high). Therefore, it could help transportation firms assess the potential effects of developing and optimizing two-part pricing schemes and of adopting and redesigning various relationship management practices on consumers' subsequent (inter-temporal) contractual choices and usage decisions.

To our knowledge, this study is the first to be based on an extensive and unique longitudinal dataset (more than four million individual customers' transactions) in the railway market that explicitly considers contractual decisions within two-part travel pricing schemes. Based on this study approach, we can develop some interesting reflections for the field of customer relationship management. The value and the efficiency of diverse forms of customer programs have been the subject of controversial discussions among researchers. For example, Leenheer et al. (2007), Meyer-Warden (2008), Noordhoff, Pauwels, and Odekerken-Schröder (2004) and Vesel and Zabkar (2009) study the characteristics of such programs and contribute to our understanding of the effectiveness and economic outcomes of loyalty programs. Despite the considerable proliferation of loyalty programs, Berman (2006) observes that many have not produced the desired results. According to Allaway et al. (2006), little is known about the responsiveness of different customer segments and about differences in the behavior patterns of customers included in such programs. In addition, in recent years the awareness of the need to improve our understanding of the outcomes of CRM practices in the transportation sector and also of the resulting opportunities to influence consumer choices more effectively has grown considerably (see Ellinger, Daugherty, and Gustin 1997; Ellinger, Daugherty, and Plair 1999; Ramanathan 2010; Steven, Dong, and Dresdner 2012 on various aspects of customer services and loyalty in logistics and transportation settings). As managers and academics become increasingly interested in the 'true' value of CRM practices, based on the evidence provided here we point out some systemic flaws in one of the biggest loyalty programs in Germany, and we can highlight some critical leverage points relevant to improving the effectiveness of loyalty programs in rail travel. Our results may suggest a direction for relationship management to take in similar transportation contexts as well.

We have highlighted the customer demographics, CRM practices, pricing strategies and BC usage factors that are most influential on consumers' upgrading, downgrading and cancellation events, and quantify their relative importance, to assist transportation firms to select the factors to focus on when trying to affect either kind of behavior among customers. Specifically, we show that on the one hand, firms might take a stronger segment-specific approach to customers with low usage (BC25) and medium usage intensity (BC50). On the other hand, results also suggest that it could pay to differentiate between customers on a demographic basis when it comes to activities targeted at reducing downgrading events. We point out opportunities to rethink CRM practices, particularly in terms of electronic mailing policies (e.g., automated mailings, and special offers), as in some circumstances, they have counterproductive effects and inhibit customer relationships. We also highlight opportunities to redesign customer loyalty programs to increase retention and upgrading behavior. We have also revealed the effects of pricing and consumers' previous contract decisions that led to optimal or suboptimal usage of their loyalty cards. Further, we observe that neither cancellation nor upgrade and downgrade hazards are 'memoryless', since change proportions of these events are affected by the track record a customer has with the firm, that is, by the time passed since the (initial) BahnCard purchase.

The contributions of the paper to the literature are: First, it adds to the recent literature on transportation and logistics management that emphasizes the growing need for customer orientation and relationship management (e.g., Ganesan et al. 2009; Grawe, Daugherty, and Dant 2012; Ramanathan 2010; Steven, Dong, and Dresdner 2012) by systematically exploring how such approaches can be managed in practice, as well as highlighting their specific effects on (un)desired business outcomes in the context of rail travel. Second, consumers' contractual choices and changes therein have not as yet been studied in the railway literature, although two-part pricing arrangements have become widespread in recent years in transportation and other sectors. The literature on (rail) transportation does not yet provide a comprehensive approach to understanding consumers' travel behavior, and particularly, the determinants of their contractual choices and usage decisions over time. Accordingly, little is known of how such decisions may effectively be influenced. A better understanding of such linkages is essential when discussing the effectiveness of CRM practices, especially in the context of customer loyalty programs, and if proposing business strategies matched to future market development in the transportation sector. We shed light on these issues and provide new theoretical insights by integrating previous research on CRM and two-part pricing schemes for the transportation sector. Third, semi-parametric proportional hazards models stratified by failure type have not previously been developed to study consumers' contractual choices in a travel behavior (competing risks) context. Based on this unconventional methodological approach (see also, Li et al. 2012; Smith 2012; Wen, Wang, and Fu 2012, for recent methodological contributions in the rail sector), our results would help transportation firms assess the potential effects of promoting, re-developing, and fine-tuning their two-part pricing schemes on consumers' subsequent contractual choices and usage decisions, both initially and over an extended period. Therefore the current research offers some practical implications for railway companies, particularly, concerning the creation and management of customer loyalty programs and customer relationship management practices when using two-part pricing schemes. Fourth, since we examined an entire population of railway passengers in Western Europe based on extensive longitudinal data, we suggest that findings should be sufficiently robust to be transferable to similar cultural and economic settings. Then, extending the focus beyond the current study context, results may also help forecast performance outcomes and have implications for policy (e.g., on CRM practices and pricing strategies) for suppliers of comparable transportation services, as well as strategic guidance for firms applying two-part pricing schemes in general (e.g., concerning customer segmentation, and effects of demographics and varying usage intensities).

However, the study is not without limitations. Future studies could potentially enhance the model framework applied here by adding insights into the consumer perspective by modeling preferences towards alternative means of travel as they relate to contractual choices. A worthwhile focus may be on underlying consumer characteristics and motivations, on cultural aspects, habits, or lifestyle choices (including for example, consumers' cultural heritage, environmental consciousness, susceptibility to social influence, household income etc.). Of course, broader changes of lifestyles and attitudes within the population would change our results as well. Nevertheless, environmental consciousness and sensitivity towards oil prices have been steadily increasing throughout the last decade, so that the factors driving consumers' travel behavior are not expected to be reversed anytime soon (Statista 2011). Still, our model could also be extended to include aspects related to the market environment and competition among infrastructure providers, thereby assessing contractual choices against the background of economic and regional equity issues in a wider context. From a methodological viewpoint, the adaption of our model towards a multi-stage approach might also prove an interesting variation in future research.

7. References

Abril, Miguel, Federico Barber, Laura Ingolotti, Miguel A. Salido, Paolo Tormos, and Arthur Lova (2008). An assessment of railway capacity. *Transportation Research Part E: Logistics and Transportation Review*, 44(5), 774–806.

Andersen, Per K., and Ornulf Borgan (1985). Counting process models for life history data: a review. *Scandinavian Journal of Statistics*, 12(2), 97–158.

Allaway, Arthur W., Richard M. Gooner, David Berkowitz, and Lenita Davis (2006). Deriving and exploring behavior segments within a retail loyalty card program. *European Journal of Marketing*, 40(11–12), 1317–1339.

Allison, Paul D. (1995). *Survival analysis using the SAS system: A practical guide*. Cary, North Carolina: SAS Istitute Inc.

Batley, Richard, Joyce Dargay, and Mark Wardman (2011). The impact of lateness and reliability on passenger rail demand. *Transportation Research Part E: Logistics and Transportation Review*, 47(1), 61–72.

Berman, Barry (2006). Developing an effective customer loyalty program. *California Management Review*, 19(1), 123–148.

Bhat, Chandra R., and Rupali Sardesai (2006). The impact of stop-making and travel time reliability on commute mode choice. *Transportation Research Part B: Methodological*, 40(9), 709–730.

Blossfeld, Hans-Peter, Alfred Hamerle, Karl U. Mayer (1986). *Ereignisanalyse: Statistische Theorie und Anwendung in den Sozialwissenschaften*. Frankfurt am Main, Germany: Campus Studium.

Blossfeld, Hans-Peter, Katrin Golsch, and Gotz Rohwer (2007). *Event history analysis with Stata*. New Jersey, USA: Taylor-Francis.

Boulding, William, Richard Staelin, Michael Ehret, and Wesley J. Johnston (2005). A customer relationship management roadmap: what is known, potential pitfalls and where to go. *Journal of Marketing*, 69(4), 155–166.

Collett, David (2003). *Modelling survival data in medical research*. New York, USA: Taylor & Francis.

Corman, Francesco, Andrea D'Ariano, Dario Pacciarelli, and Marco Pranzo (2010). A tabu search algorithm for rerouting trains during rail operations. *Transportation Research Part B: Methodological* 44(1), 175–192.

Corman, Francesco, Andrea D'Ariano, Dario Pacciarelli, and Marco Pranzo (2012). Optimal inter-area coordination of train rescheduling decisions. *Transportation Research Part E: Logistics and Transportation Review*, 48(1), 71–88.

Cox, David R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society, Series B*, 34(2), 187–220.

Daugherty, Patricia J., Haozhe Chen, Daniel D. Mattioda, and Scott J. Grawe (2009). Marketing/logistics relationships: influence on capabilities and performance. *Journal of Business Logistics*, 30(1), 1–18.

Della Vigna, Stefano, and Ulrike Malmendier (2004). Contract design and self-control: theory and evidence. *Quarterly Journal of Economics*, 119(2), 353–402.

Della Vigna, Stefano, and Ulrike Malmendier (2006). Paying not to go to the gym. *American Economic Review*, 96(3), 694–719.

Ellinger, Alexandeer E., Patricia J. Daugherty, and Craig M. Gustin (1997). The relationship between integrated logistics and customer service. *Transportation Research Part E: Logistics and Transportation Review*, 33(2), 129–138.

Ellinger, Alexandeer E., Patricia J. Daugherty, and Qunetin J. Plair (1999). Customer satisfaction and loyalty in supply chain: the role of communication. *Transportation Research Part E: Logistics and Transportation Review*, 35(2), 121–134.

Fan, Terence P.C. (2009). Determinants of de novo new entrant survival in the liberalized intra-European scheduled passenger airline industry. *Transportation Research Part E: Logistics and Transportation Review*, 45(2), 293–306.

Fine, Jason, and Robert J. Gray (1999). A proportional hazards model for the subdistribution of a competing risk. *Journal of the American Statistical Association*, 94(446), 496–509.

Ganesan, Shankar, Morris George, Sandy Jap, Robert W. Palmatier, and Barton Weitz (2009). Supply chain management and retailer performance: emerging trends, issues, and implications for research and practice. *Journal of Retailing*, 85(1), 84–94.

Grambsch, Patricia M., and Terry M. Therneau (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*, 81(3), 515–526.

Grawe, Scott J., Patricia J. Daugherty, and Rajiv P. Dant (2012). Logistics service providers and their customers: gaining commitment through organizational implants. *Journal of Business Logistics*, 33(1), 55–63.

Hansen, Ingo (2007). Advanced modelling of train operations in stations and networks. *Transportation Research Part B: Methodological*, 41(2), 145–147.

Hess, Stephane, Thomas Adler, and John W. Polak (2007). Modelling airport and airline choice behavior with the use of stated preference survey data. *Transportation Research Part E: Logistics and Transportation Review*, 43(3), 221–233.

Hosmer, David W., and Stanley Lemeshow (1999). *Applied survival analysis: Regression modelling of time to event data*. New York, USA: John Wiley & Sons.

Iliescu, Dan C., Laurie A. Garrow, and Roger A. Parker (2008). A hazard model of US airline passengers' refund and exchange behavior. *Transportation Research Part B: Methodological*, 42(3), 229–242.

Jain, Dipak C., and Naufel J. Vilcassim (1991). Investigating household purchase timing decisions: a conditional hazard function approach. *Marketing Science*, 10(1), 1–23.

Jeong, Jong-Hyeong, and Jason P. Fine (2007). Parametric regression on cumulative incidence function. *Biostatistics*, 8(2), 184–196.

Kalbfleisch, John, and Ross L. Prentice (2002). *The statistical analysis of failure time data*. New York, USA: Wiley.

Kaplan, Edward L., and Paul Meier (1958). Nonparametric estimation from incomplete observations. *Journal of the American Statistical Association*, 58(282), 457–481.

Keumi, Chikako, and Hideki Murakami (2012). The role of schedule delays on passengers' choice of access modes: A case study of Japan's international hub airports. *Transportation Research Part E: Logistics and Transportation Review*, 48(5), 1023–1031.

Leenheer, Jorna, Harald J. van Heerde, Tammo H.A. Bijmolt, and Ale Smidts (2007). Do loyalty programs really enhance behavioural loyalty? An empirical analysis accounting for self-selecting members. *International Journal of Research in Marketing*, 24(1), 31–47.

Lee, Bachjin, and Harry J. P. Timmermans (2007). A latent class accelerated hazard model of activity episode durations. *Transportation Research Part B: Methodological*, 41(4), 426–447.

Light, Audrey, and Yoshiaki Omori (2012). Fixed effects maximum likelihood estimation of a flexibly parametric proportional hazard model with an application to job exits. *Economics Letters*, 116(2), 236–239.

Li, Zhi-Chun, William H.K Lam, Roderick S.C. Wong, and Agachai Sumalee (2012). Design of a rail transit line for profit maximization in a linear transportation corridor. *Transportation Research Part E: Logistics and Transportation Review*, 48(1), 50–70.

Lin, Bo-Lin, Zhi-Mei Wang, Li-Jun Ji, Ya-Ming Tian, and Guo-Qing Zhou (2012). Optimizing the freight train connection service network of a large-scale rail system. *Transportation Research Part B: Methodological*, 46(5), 649–667.

Lunn, Mary, and Don McNeil (1995). Applying Cox regression to competing risks. *Biometrics*, 51(2), 524–532.

Meyer-Warden, Lars (2008). The influence of loyalty programme membership on customer purchase behaviour. *European Journal of Marketing*, 42(1–2), 87–114.

Noordhoff, Corine, Pieter Pauwels, and Gaby Odekerken-Schröder (2004). The effect of customer card programs: A comparative study in Singapore and the Netherlands. *International Journal of Industry Management*, 15(4), 351–364.

O'Quigley, John, Ronghui Xu, and Janez Stare (2005). Explained randomness in proportional hazards models. *Statistics in Medicine*, 24(3), 479–489.

Putter, Hein, Marta Fiocco, and Ronald B. Geskus (2007). Tutorial in biostatistics: competing risks and multi-state models. *Statistics in Medicine*, 26(11), 2389–2430.

Ramanathan, Ramakrishnan (2010). The moderating roles of risk and efficiency on the relationship between logistics performance and customer loyalty in e-commerce. *Transportation Research Part E: Logistics and Transportation Review*, 46(6), 950–962.

Reinartz, Werner J., Manfred Krafft, and Wayne D. Hoyer (2004). The CRM process: its measurement and impact on performance. *Journal of Marketing Research*, 41(3), 293–305.

Schmale, Hendrik, Thomas Ehrmann, and Alexander Dilger (2013). Buying without using: biases of German BahnCard buyers. *Applied Economics*, 45(7), 933–941.

Sarstedt, Marko, Sebastian Scharf, Alexander Thamm, and Michael Wolff (2010). Die Prognose von Serviceintervallen mit der Hazard-Raten-Analyse: Ergebnisse einer empirischen Studie im Automobilmarkt. *Zeitschrift für Planung und Unternehmenssteuerung*, 20(3), 269–283.

Smith, Andrew S. J. (2012). The application of stochastic frontier panel models in economic regulation: experience from the European rail sector. *Transportation Research Part E: Logistics and Transportation Review*, 48(2), 503–515.

Statista (2011). *Fakten und Zahlen zum deutschen Reisemarkt 2011*. Berlin: Statistisches Bundesamt.

Steven, Adams B., Yan Dong, and Martin Dresdner (2012). Linkages between customer service, customer satisfaction and performance in the airline industry: Investigation of non-linearities and moderating effects. *Transportation Research Part E: Logistics and Transportation Review*, 48(4), 743–754.

Vach, Werner (2005). The analysis of competing risk data: A guided tour. *Statistics in Medicine*, 132(4), 1–41.

Vesel, Patrick, and Vesna Zabkar (2009). Managing customer loyalty through the mediating role of satisfaction DIY retail loyalty program. *Journal of Retailing and Consumer Services*, 16(5), 396–406.

Wen, Chieh-Hua, Wei-Chung Wang, and Chiang Fu (2012). Latent class nested logit model for analyzing high-speed rail access mode choice. *Transportation Research Part E: Logistics and Transportation Review,* 48(4), 545–554.

III. Learning Effects in Loyalty Programs: Performance Impacts of Decision-Making Behavior and Pricing

"Knowledge would be fatal. It is the uncertainty that charms one. A mist makes things wonderful."
Oscar Wilde (1854-1900)

1. Abstract

The success of customer loyalty programs enhances customer loyalty. Their success assumably depends on how consumers accept, use, and particularly *learn* to use their corresponding loyalty cards. Based on a comprehensive data set of German railway customers we analyze the structure of consumer learning curves in low- and high-price contexts. Further, this research illustrates the linkages of loyalty card usage, learning, and pricing issues to cancellation behavior, and highlights multiple effect changes over time. It is shown that learning effects and pricing strategies do have an impact on cancellation rates and their influence changes with ongoing contract duration. For structuring customer loyalty programs, the implication for marketing managers is to consider behavior patterns as a result of tariff arrangements and to facilitate learning how to correctly use the loyalty cards, thus leading to associated higher retention rates, and firm performance.

2. Introduction

The concepts of customer loyalty and retention have been intensively discussed from a plurality of perspectives. Predominantly, customer satisfaction, price, presence of competition, switching costs, and variables describing the customer service experience are considered in this context. Kotler (1994), for instance, regards customer satisfaction as the 'key to customer retention', whereas Hennig-Thurau and Klee (1997) even more explicitly describe the link between customer satisfaction and long-term retention of customers as the 'starting point' rather than the core question of the analysis. Several research attempts delve into other specific determinants of customer behavior and attitudes in terminating customer relationships, at this, the role of *consumer learning* in connection with loyalty card usage and its interrelationship to price (perceptions) remains completely unexplored. Our study addresses this research gap by analyzing the following questions: how can learning (and also unlearning) in loyalty programs be described? Is learning in such programs related to pricing issues? How do learning effects impact loyalty? Do these effects change over time?

We argue that understanding a loyalty card system during the usage process (and particularly adopting a more appropriate way of usage) can play a significant role in constituting customers' lifecycles and hence involve useful performance implications for firms employing such loyalty programs. Accordingly, we try to provide evidence about the nature of learning curves in a railway two-part pricing context, and the impact of learning effects, (non-) optimality of choice and pricing issues on cancellation activities from customer perspective, and subsequently derive practical recommendations for marketers.

As many costumer products, a loyalty card entails (physical) usage to derive benefits. The way a costumer interacts with and learns to use these products are said to be critical in product adoption (Robertson and Gatignon 1986; Shih and Venkatesh 2004) and in defining the customer experience (Dahl and Moreau 2007; Moreau and Dahl 2005). We assume that product usage, i.e. product experience, and the subsequent adaptability throughout the customer lifecycle is neatly connected to the assessment of quality and thereby satisfaction, which is associated with the initially unknown usage intensity. At this, in many industries customers are confronted with two-part pricing schemes (e.g., in the context of customer loyalty cards), and supposed to choose the tariff most appropriate to their expected usage behavior. Often they run the risk of a selection bias, i.e. tariff choice and consumption differ. Drawing on empirical evidence, Nunes (2000) explains how customers integrate usage expectation into the decision process when choosing between paying per use and paying a flat fee for unlimited access. They tend to compare the subjective likelihood of using more than the break-even volume with the subjective likelihood of using less. In this connection, he finds that costumers habitually overestimate the likelihood of using enough to justify the flat-rate and thus falsely favour this payment plan. The perceived range of usage thereby strongly affects the costumers' misperceptions. Other famous examples of studies examining flat rate biases are provided by Thaler (1999), Della Vigna and Malmendier (2006), Lambrecht and Skiera (2006), Goettler and Clay 2011, and Schmale, Ehrmann, and Dilger (2013). However, customers can *learn* over time how to correctly use their loyalty cards which we assume, is connected to enhanced customer satisfaction, and hence positively influences retention rates. Of course, customers can also *unlearn* optimal, i.e. rational, usage which should have contrary effects on customer retention. For example, Narayanan, Chintagunta, and Miravete (2007) analyze the usage of a local telephone service and find that customers learn about their own usage patterns and switch plans to save costs where necessary. Our context is also one where customers make a decision under uncertainty and thus end up making choices that are potentially non-optimal ex post.[8] We investigate the structure of (un)learning curves in low and high-price contexts, study (un)learning effects concerning the usage of loyalty cards as well as the rationality of buying decisions in the context of two-part tariff systems and explore the relationship to cancellation behavior empirically.

[8] Concerning the outcomes of consumer choice, we also refer to Levav, Kivetz, and Cho (2010). They show that compatibility with more than one attribute arouses acute decision conflict and evokes decision processes that result in a pronounced tendency to make "counter-normative choices", whereas incompatibility with a product's attributes leads to choosing extreme alternatives, which suggests the presence of a "pick-your-poison" effect.

This paper is structured as follows: after a brief introductory note on (organizational and customer) learning, we describe the characteristics of our dataset, the key variables used, and define customer learning in the context of loyalty card usage. Our research is tripartite. The layout of studies is depicted in Figure12. In study 1, we first analyze the structure of learning and 'unlearning' curves for the use of loyalty cards in both low- and high-prize contexts. Study 2 is based on the cancellation event: we illustrate the connection to learning and constitute its linkages towards pricing issues, point of usage (PoU)[9] and usage behavior. In study 3, we empirically investigate how the above-mentioned impact factors (particularly learning) affect cancellation events, and how their effect changes over time, using a sequential logit model.

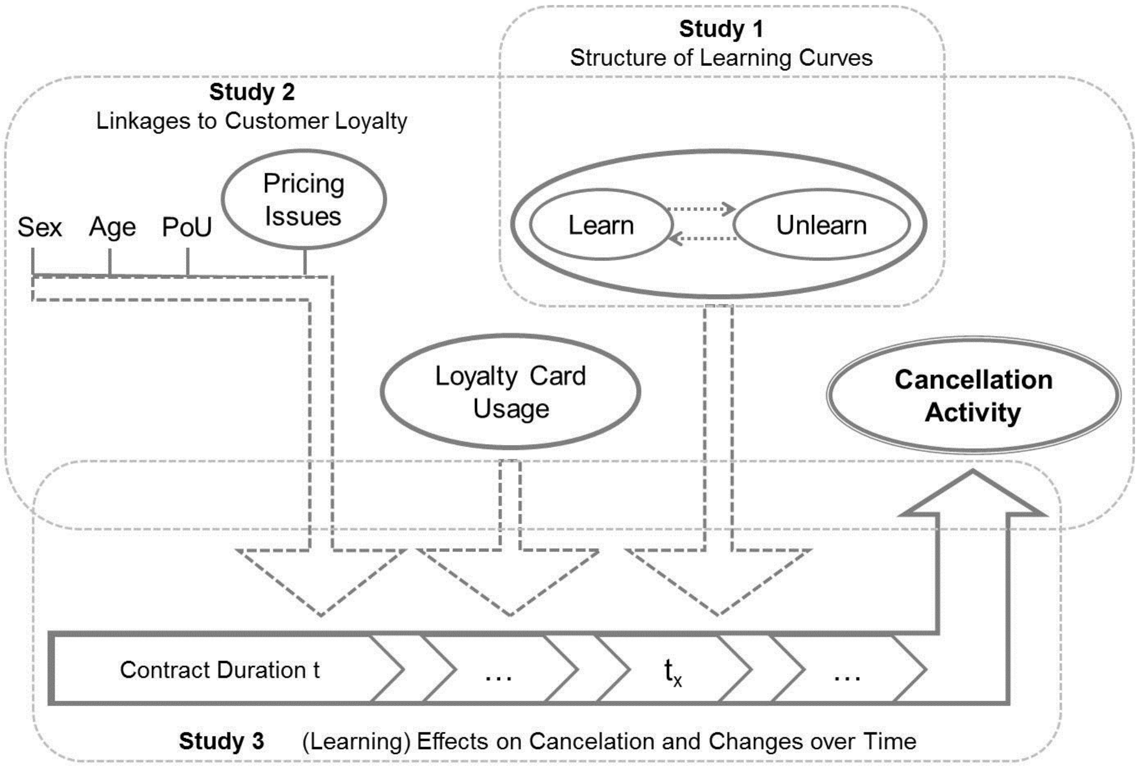


Figure 12. *Conceptual Overview and Layout of Studies*

9 We denote the contact point, i.e. ticket purchases via the Internet or from the counter, with the term 'point of usage'.

The research described here contributes to extant knowledge in three ways. First, we outline a different assessment of learning – in terms of rational decision making, i.e. optimality of product choice – and contrast it with the traditional views of (consumer) learning. Our research suggests that consumers' ability (or willingness) to adopt appropriate usage behavior depends on the price-context. At this, we disprove that the structures of learning and unlearning curves are characterized by an inverse relationship. Second, we draw on cancellation events and their linkages to the way and point of usage, as well as learning and pricing aspects to explicate 1) their role for the success of loyalty card programs (two-part pricing schemes), 2) the importance of product adoption over time, and 3) corresponding behavioral consequences, e.g. concerning the perception of prices or the relevance of different distribution channels. Our findings suggest that learning facilitates a prolongation of contracts (most important in the first three years). Also point of usage and current (and not past) usage explain loyal behavior, and especially in the low-price context the concept of perceived price-fairness by Xia, Monroe, and Cox (2004) proves of value. Third, this research is the first in marketing to investigate the development of learning effects and pricing issues related to customer loyalty in the context of two-part pricing schemes for railway customers. Analyzing a comprehensive longitudinal dataset, we shed light on the impact of customer learning over time, and provide evidence about its relevance for customer relationships.

3. Concept of Learning and the Gateway to the Data at Hand

3.1 (Un)Learning to Use Loyalty Cards

The impact and interdependency of organizational learning on customer satisfaction and loyalty has been intensively analyzed for several decades.[10] In this connection, the discussion predominantly focused on intra-corporate perspectives (e.g. intra- and inter-organizational learning curves). Levitt and March (1988), Brown and Duguid (1991), Huber (1991), March (1991), or Argyris (1999) explore the fundamental theory and provide first empirical evidence on organizational learning. In this study, we choose a customer-centric approach towards learning. Babutsidze (2011), for instance, discusses two sources of consumer skill acquisition, *learning by consuming* and *consumer socialization process.* Latter was initiated by Ward (1974) and – inter alia – has been considered, extended and further discussed by Moschis and Churchill (1978), and Churchill and Moschis (1979). The former is comprised by the concept of *consumer learning.* A comprehensive overview of this research field is provided by Lakshmanan and Krishnan (2011). Here, predominant focus of the considered approaches is on isolating and quantifying consumer learning (usually of quality of a product) as a factor in purchase behavior change time. In the course of this study, we interpret consumer learning as a factor in usage behavior change time in the context of two-part pricing schemes. Assigning this type of (adaptive) learning primarily to *procedural* knowledge (primarily related to *how* to do things; Squire 1986), and to a lesser degree to *declarative* roots (e.g., benefit associations or knowledge of product attributes; Van Osselaer and Janiszewski 2001), we simply measure a consumer's (discontinuous) learning and unlearning by recording a change of states between usage categories. This is related to the findings by Miravete (2002) who finds evidence for learning by consumers about their usage levels.

Our dataset exhibits different usage patterns – between different customers as well as within the contract duration of particular loyalty card owner owners. Based on demographical characteris-

[10] In the following we will use the term 'customer' and 'consumer' interchangeably, since the consumption of the underlying product in this study is implicitly characterized by (repeat) purchases of railway tickets.

tics like sex and age, the price paid for a loyalty card and the way of handling it, we analyze the nature of learning curves of low and high-price contexts concerning the loyalty card usage, investigate how a customer's adaptability and learning aptitude affects the cancelling behavior and particularly study how these learning effects change over time. We interpret customer learning as the capability to adapt the way of usage of a loyalty card in terms of changes towards an 'optimal', i.e. rational, usage behavior (accordingly unlearning as a change to irrational usage behavior)[11] and subsequently examine its linkage to customer loyalty and its effects changes throughout the contract duration time.

3.2 Contractual Options and Key Variables

We analyze data provided by the major German railway company Deutsche Bahn AG (DB) which contain a comprehensive travel history of the railway customers taking part in its customer loyalty program and capture the space of time from December 2002 till July 2008. This large-scale, unique longitudinal dataset comprises more than four million transactions of over 300,000 customers, each being related to one of approximately 800,000 loyalty cards ('BahnCards'). These BahnCards enable railway customers to travel at discount prices for an up-front fee during the contract period. DB customers can basically choose between three contracts: BahnCard25 (BC25 in the following), BahnCard50 (BC50) and BahnCard100 (BC100), providing price reductions of 25%, 50% and 100% on fares, respectively. Each contract is available for the 1st or the 2nd class. However, some adjustments were necessary to enhance reliability of the data base. First, we excluded all loyalty program members whose overall lifetime sales volume did not exceed zero. Furthermore, we dropped all customers with inconsistent, defective, or not clearly assignable contracts.[12] Overall, we concentrate on customers with 2nd class BahnCards to achieve a maximum comparability between contracts. Our final sample features

[11] This formulation is in line with previous current research defining learning as a regular shift in behavior or knowledge informed by prior action (Argote, 1999; Bingham and Davis 2012; Cyert and March, 1963; Levitt and March1988; Mine, Bassoff, and Moorman, 2001).

[12] Possible reasons for deficiencies in the dataset might be goodwill cancellations, accounting or registration errors.

the history of BC25 and BC50 customers.[13] Particularly, the following variables are employed: *cancel1, ..., cancel5* indicating whether a customer terminated her contract in the respective year of usage, demographical information *sex* and *age*, indicator variables *counter1, ..., counter5* and *internet1, ..., internet5,* defining whether tickets were bought from the counter or via the Internet in the respective year of usage. The numerical variables *price1, ..., price5* determine the price of the particular BahnCard in its respective year of usage. The variables *discount1, ..., discount5* indicate, whether tickets were combined with special offers in the respective year of usage. Latter is only implemented for BC25 customers, since budget prices cannot be combined with a BC50.

The binary variable *usage* is calculated according to optimality boundaries (see Appendix A), comprising two parameters: the first indicating suboptimal, the second indicating beyond optimal usage. For the implementation of learn variables, we differentiate between learning and unlearning effects: a change from suboptimal or beyond optimal BahnCard usage towards an optimal card usage from one year of usage to another is marked with 1 in the category 'learn' (and 0 otherwise), and accordingly, a reverse change (from optimal to beyond or suboptimal usage in two successive years) is incorporated with 1 in the category 'unlearn' (and 0 otherwise). Both effects 'learn' and 'unlearn' are captured in the variables *learn1*, …, *learn5* (*learn3=(0,0),* for instance, describes that there were neither learning nor unlearning effects from year 3 of usage in comparison to year 4). According to the definition of customer learning (and respective scaling) used here, which predominantly refers to the adoption of rational usage behavior, learning is monitored in a rather discontinuous way. Against this background, collective learn rates and their delineation over time constitute the following analysis.

[13] Since BC100 users do not purchase any tickets, their travel behavior cannot be monitored. Discussing how efficiently BC100 contracts are used is not an issue of this paper.

4. Study 1: The Structure of Collective Learning and Unlearning Curves for Loyalty Cards

The consideration of unlearning complements the large body of work emphasizing learning from success and contributes to the further development of the emerging experiential learning-from-failure perspective (Baum and Dahlin 2007; Chuang and Baum 2003; Denrell 2003; Haunschild and Rhee 2004; Haunschild and Sullivan 2002; Kim 2000; Miner et al. 1999). Learning to optimally use a loyalty card might be driven by other factors than unlearning it (e.g., usage experience, willingness to adopt, rational mind-set,… vs. misjudgment, over-estimation bias, irrationality,…).[14] Hence, we think that the structure of the learning curve can be distinguished from the unlearning curve in its corresponding price-segment. Further, we assume that realizing an 'optimal' usage behavior is somewhat easier in a low-prize (versus high-prize) context, although the same should apply for unlearning to optimally use a BahnCard. Combining the preceding two expectations, formally, we hypothesize the following:

> H_{1a}: *The structure of the average learning curve for loyalty card usage differs from the structure of the average unlearning curve.*
>
> H_{1b}: *The structures of (un-)learning curves for loyalty card usage vary across low- and high-price contexts.*

4.1 Method

We analyze how the share of those customers who learn and of those who unlearn (according to the scheme described above) develops during the contract duration. For each year of usage we identify the share of customers who 'learn' to optimally use their BahnCard in comparison to the preceding year. The same is done for the 'unlearners'. In doing so, we treat BC25 and BC50 customers separately. Finally, we use an unpaired, two-sample mean-comparison test (t-test) to compare the values of the different years for both low- and high-price context (i.e. BC25 and BC50). Based on the t-test results we provide empirical evidence on the structure of learning

---

[14] It might be worth noting that in our study an illustration of learning curves seems more useful at the collective level.

and unlearning curve in this railway context, and compare the outcomes between the two customer segments.

4.2 Results

The learn rate in the low-price segment, i.e. among the BC25 customers, slightly decreases over time, although it remains on a similar level throughout contract duration. We observe an average share of learners of 8.90 % (n = 1,684) in the second usage period in comparison to the first, which declines to a share of 6.98 % (n = 193) at the end of the sixth year of usage in comparison to the fifth. The corresponding test results (M_{Learn_i} vs. M_{Learn_i+1}; t-value; *p*-value) are: (M_{Learn1} = .1042079 vs. M_{Learn2} = .0907122; t = 3.6689; $p < 0.001$), (M_{Learn2} = .0907122 vs. M_{Learn3} = .088785; t = 0.4578; $p < 0.05$), (M_{Learn3} = .088785 vs. M_{Learn4} = .0770071; t = 2.4189; $p < 0.01$), (M_{Learn4} = .0770071 vs. M_{Learn5} = .0697506; t = 1.1848, $p < 0.05$). The development of the unlearn rate exhibits a u-shaped structure. The share of unlearners after two years amounts to 16.07 % (n = 2,771). This value decreases until the end of the fourth usage period (9.10 %, n = 722) and slightly grows again to 10.31% (n = 296) in the end of the sixth usage period. The corresponding t-test results are as follows: ($M_{Unlearn1}$ = .1606656 vs. $M_{Unlearn2}$ = .1105421; t = 11.9448; $p < 0.0001$), ($M_{Unlearn2}$ = .1105421 vs. $M_{Unlearn3}$ = .0909664; t = 4.4115; $p<0.0001$), ($M_{Unlearn3}$ = .0909664 vs. $M_{Unlearn4}$ = .0922113; t = -0.2472; $p > 0.1$), ($M_{Unlearn4}$ = .0922113 vs. $M_{Unlearn5}$ = .1031359; t = -1.6153; $p < 0.05$). The t-tests reveal different structures of learning and unlearning curves among the BC25 customers, providing direct support for H_{1a} concerning the low-price segment.

For the BC50-customers the learn rate turns out to be u-shaped (but on a relatively stable level), whereas the t-test reveals a slightly decreasing unlearn rate over contract duration. The share of learners decreases from 10.14 % (n = 2,157) slightly decreases to 8.95 % (n = 681) at the end of contract year four and raises to 10.00 % (n = 433) in the subsequent year. Corresponding t-test results are given by (M_{Learn1} = .1014438 vs. M_{Learn2} = .0991457; t=0.6823; $p < 0.05$), (M_{Learn2} = .0991457 vs. M_{Learn3} = .0894758; t=2.2715; $p < 0.05$), (M_{Learn3} = .0894758 vs. M_{Learn4} = .1000231; t= -1.9051, $p < 0.05$). From the second year of usage the share of unlearners continuously decreases from 15.51 % (n=2964) to 9.80 % (n=382). The corresponding t-tests provide ($M_{Unlearn1}$ = .1551345 vs. $M_{Unlearn2}$ = .1248477; t = 7.3192; $p < 0.0001$), ($M_{Unlearn2}$ = .1248477 vs. $M_{Unlearn3}$ = .1079365; t = 3.4415 ; $p < 0.001$), ($M_{Unlearn2}$ = .1079365 vs. $M_{Unlearn3}$ = .0980493; t = 1.6150; $p < 0.05$). Also in the high-price segment (BC50), we detect different structures of learning and unlearning curve.

Thus, the structure of the average learning curve differs from the structure of the average unlearning curve in both costumer segments BC25 and BC50, and the structure of learning curves as well as of the unlearning curves varies across low- and high-price contexts, providing full support for the hypotheses H_{1a} and H_{1b}.

4.3 Discussion

The results of this study indicate that learning, in terms of the adoption of rational usage behavior, is deeply connected to the price context. The willingness to learn seems considerably stronger in the high-price context. Especially in the low-price segment, the share of unlearners always exceeds the share of learners. This is not the case in the high-price segment: since the learn rate remains on a relatively stable level, the unlearn rate reaches a level below the learn rate after more than 5 years of contract duration. Apart from the influence of price levels on usage adoption, we find another interesting aspect concerning the nature of learning curves. According to our scaling of parameters, a learning customer can be regarded as the opposite of an unlearning customer. But we find that learning and unlearning curves are not described by an inverse relationship. The reason might be different drivers that facilitate learning in comparison to unlearning.

Still, it has to be mentioned that about 75-85 % of the customers do not exhibit any learning or unlearning effects in the respective years of usage. Those keep on using their BahnCard in the same way as the preceding year – either non-optimally or optimally.

The next study examines the role of this subgroup concerning the determinants of contract cancellations. We also lay out and test our expectations regarding the linkages to BahnCard prices and usage behavior in this loyalty program context.

5. Study 2: Learning, Usage and Pricing Issues and Their Linkage to Customer Loyalty

A general assessment of the linkages of learning, pricing aspects, the point of usage and customer loyalty card usage to customer cancellation behavior is in the focus of this study. Hence study 2 picks up the findings of study 1 and links them to cancellation events. We analyze the customer termination rate during contract duration and provide further empirical evidence how learning impacts customer loyalty. In this connection, we also examine how PoU and pricing issues, e.g. low- or high-prize context or price elasticity, drive the risk of cancellation.

First, we examine the annual development of churn rates over contract duration. According to the observations made by Iliescu, Garrow, and Parker (2008) concerning the airline industry, that higher cancellation rates are generally realized for recently purchased tickets, we assume that this should apply for the customer railway sector. Formally,

> *H_{2a}: The share of contract cancellations decreases with the duration of loyalty card contracts.*

One main objective of this study is to establish the dependency between customer learning and customer loyalty in the railway context. Iyengar, Ansari, and Gupta (2007) conduct several policy experiments to capture the effects of customer learning, pricing, and service quality on customer lifetime value and find that customer leaning can result in a win-win situation, identifying the change in retention rate with and without learning as a key driver. Extending their findings to unlearning, we hypothesize the following:

> *H_{2b}: The retention rate of loyalty card contracts is higher (lower) for learners (unlearners) than for 'non-learners'.*

Here, interpret 'non-learning' customers as those customers who do neither learn nor unlearn in the respective contract period under investigation.

Researchers have identified various determinants of customers' disloyalty (see also above). The role of learning has not yet been considered in a loyalty program context. According to the findings by Iyengar, Ansari, and Gupta (2007) and as a consequence from hypothesis H_{2b}, the learning effects are assumed to contribute significantly towards an explanation of the termination behavior. Thus:

> *H_{2c}: Learning effects influence the cancellation of a loyalty card.*

Additionally, we assume that the contact point, from which customers choose to buy railway tickets, could have an effect on cancellation events. Particularly, Grewal and Levy (2009) highlight the coordination of online and offline channels as an emerging issue of compelling interest to (e-tailing) research which is expected to continue to grow. We examine the cases of counter and Internet purchase, and expect that the usage of the BahnCard both in online as well as offline channels should affect its contract termination.

> *H_{3a}: The counter activity during the usage period(s) has an impact on the cancellation of a loyalty card contract.*
>
> *H_{3b}: The Internet purchases during the usage period(s) have an impact on the cancellation of a loyalty card contract.*

Another objective of this study is to elucidate the role of price, price sensitivity and perceived price fairness in the context of customer retention in loyalty programs. Choi et al. (2006) provide evidence for the effect of customer (dis-)loyalty on customer price sensitivity and find that price sensitivity is negatively influenced by an increase in loyal behavior. We expect to approve this observation, and thus hypothesize:

> *H_{4a}: Price sensitivity has an impact on the cancellation of a loyalty card contract.*

We also assume that the price of a BahnCard impacts the cancellation of a contract. Here, we refer to the concept of price fairness (e.g. Bolton, Warlop, and Alba 2003) which involves a comparison of a price (or procedure) with a pertinent standard, reference, or norm, i.e. the initial price of a BahnCard. In their conceptual framework of price fairness Xia, Monroe, and Cox (2004) formulate two perceptions concerning transaction similarity and choice of comparison party: First, given a perceived price discrepancy between two transactions, a high degree of transaction similarity leads to a high perception of price unfairness. Second, given a perceived price discrepancy and two transactions with similar characteristics, when available, has a greater effect on price unfairness judgments than does the buyer's self-reference. We assume that this can be applied to the loyalty cards context. Thus:

> *H_{4b}: The initial price of a loyalty card has an influence on its cancellation.*
>
> *H_{4c}: The subsequent annual fees to prolong the existing contract have an impact on the cancellation of a loyalty card contract as long as they exceed the initial price paid for it.*[15]

Apart from motivational aspects of pricing issues, customer experience over time should also provide a breeding ground for the adaption of the way of usage, and thus, learning (or unlearning) effects. The way of current usage could be the result of path- dependencies, but does not necessarily have to be. Hence, current way of usage could be triggered by foregoing ways of usage or by other contingent factors. Accordingly, we expect the past, and particularly the current way of usage of a loyalty card (in terms of rational decision making) to be a key driver for contract cancellation in this learning context. This is formulated in the following two hypotheses:

> *H_{5a}: Current way of usage of a loyalty card influences contract cancellation.*
>
> *H_{5b}: Past way of usage of a loyalty card influences contract cancellation.*

5.1 Method

We calculate collective annual cancellation rates of all customers (BC25 and BC50), and for the subsegments of the learning as well as the unlearning customers, being in their n^{th} year of BahnCard usage respectively. For the comparison of cancellation rates between the different usage periods, we use unpaired, two-sample mean-comparison tests (t-tests) (H_{2a} and H_{2b}).

---

[15] In the following periods after initial purchase, the customers in our sample cannot influence the price of the subsequent loyalty card (here: BahnCard). In case of non-termination the up-to-date standard price is charged respectively.

To describe the linkages of learning effects, PoU, pricing issues and usage quality to cancellation events over time, we use chi-square tests of independence for each year of BahnCard contract duration and show which parameters can be statistically associated with contract cancellation activities and where applicable, how some effects change over time (H_{3a} - H_{5b}). Particularly concerning hypothesis H_{4a}, we measure price sensitivity in the following way: Since a BahnCard25 can be combined with special offers we mark customers who make use of discount prices as 'price sensitive' and analyze the link of price sensitive customers to contract duration. In order to achieve an acceptable sample size for all contract periods we only consider four contract periods in the cancellation context.

5.2 Results

This study seeks to establish several linkages to contract cancellation events. Hypothesis H_{2a} refers to the question how the cancellation rate changes over time. We find that the share of terminating customers decreases with the duration of the BahnCard contract – for both low- and high-prize contexts. In the BC25 customer segment the cancellation rate falls from 17.0 % (n = 26,952) to 9.72 % in the end of contract year four (n = 8,820). The corresponding t-tests yield (analogously to study 1) ($M_{Cancel1}$ = .1700059 vs. $M_{Cancel2}$ = .1597366; t = 2.9286; $p < 0.01$), ($M_{Cancel2}$ = .1597366 vs. $M_{Cancel3}$ = .1174732; t = 10.5347; $p < 0.0001$), ($M_{Cancel3}$ = .1174732 vs. $M_{Cancel4}$ =.0971655; t = 4.6884; $p < 0.0001$). For the BC50 customers the cancellation rate exceeds the rate in the low-price context. In this segment, the cancellation share continuously decreases from 23.01 % (n = 28813) after contract year one to 12.64 % (n = 7737) after contract year four. Testing whether the difference of the cancellation shares of two subsequent years is positive, results in ($M_{Cancel1}$ = .2301063 vs. $M_{Cancel2}$ = .1679201; t = 17.1421; $p < 0.0001$), ($M_{Cancel2}$ = .1679201vs. $M_{Cancel3}$ = .133968; t = 8.4353; $p < 0.0001$), ($M_{Cancel3}$ = .133968 vs. $M_{Cancel4}$ = .1264056; t = 1.5585; $p < 0.05$). Thus, hypothesis H_{2a} is fully supported.

We ascertain that the retention rate is significantly higher for learners than for 'non-learners' in both low- and high-price contexts. (M_{Learn} = .1027316 vs. $M_{NoLearn}$ = .1644791; t = -6.5829; $p <$ 0.0001), (M_{Learn} = .0527363 vs. $M_{NoLearn}$ = .1244789; t = -6.7364; $p < 0.0001$), (M_{Learn} = .0739687 vs. $M_{NoLearn} = .1013167$; $t = -2.3192$; $p < 0.01$), ($M_{Learn} = .0401891$ vs. $M_{NoLearn} = .0881657$; $t = -3.4118$; $p < 0.001$) are the test results for the BC25 customers. For the BC50 customer segment we achieve ($M_{Learn} = .0908669$ vs. $M_{NoLearn} = .1634246$; $t = -8.7662$; $p < 0.0001$), ($M_{Learn} = .0671937$ vs. $M_{NoLearn} = .1313252$; $t = -6.5308$; $p < 0.0001$), ($M_{Learn} = .26417$ vs. $M_{NoLearn} = .1315108$; $t = -6.0449$; $p < 0.0001$). Surprisingly, the inverse relationship only accounts for the high-price segment: the cancellation rate is significantly higher for the unlearners in comparison with the 'non-learners' ($M_{Unlearn} = .26417$ vs. $M_{NoUnlearn} = .1634246$; $t = 13.2087$; $p < 0.0001$), ($M_{Unlearn} = .2264808$ vs. $M_{NoUnlearn} = .1313252$; $t = 9.6651$; $p < 0.0001$), ($M_{Unlearn} =.1737968$ vs. $M_{NoUnlearn} = .1315108$; $t = 3.1877$; $p < 0.001$). This is also the case for unlearners in the first two BC25 contract years ($M_{Unlearn} =.1833273$ vs. $M_{NoUnlearn} = .1644791$; $t = 2.4344$; $p < 0.01$). After that, we do not find any significant differences between cancellation rates of unlearners and 'non-learners' (even at 0.1-level). In sum, we find full support for hypothesis H_{2b} in the high-prize context and mixed support in the low-price context.

We do not find full support for H_{2c} that learning effects influence the cancellation of a BahnCard, regardless when (during the customer life cycle) and how (learn, unlearn) they appear. They do have an impact on cancellation, but the impact changes over time. As the chi-square test results show, learning and unlearning effects are of particular importance in the first three years of usage (BC25: Pearson $\chi^2_{Learn1Cancel2} = 54.1510$, $\chi^2_{Learn1Cancel3} = 14.5490$, $\chi^2_{Learn2Cancel3} = 44.9323$, $p < .001$ respectively; BC50: Pearson $\chi^2_{Learn1Cancel2} = 48.8262$, $\chi^2_{Learn1Cancel3} = 12.0344$, $\chi^2_{Learn2Cancel3} = 23.7309$, $p < 0.01$ respectively)[16]. '*Late*' learning effects, i.e. (un-)learning after more than three years of contract duration, play a minor role to determine cancellation events. Hence the hypothesis H_{2c} is only partially supported.

The examination of the linkage between PoU and contract cancellation reveals to some extent surprising results. Confirmative to hypothesis H_{3a} we find that counter activity, i.e. buying tickets via a counter, can be statistically associated with cancellation behavior for both low- and

[16] $\chi^2_{Learn_i,Cancel\_j}$ represents the Pearson chi-square value associated with a learning effect after i+1 years of contract and a cancellation event after j years.

high-price contexts in every year of contract duration (BC25 (Pearson $\chi^2_{Counter_i,Cancel\_j}$, p-value): $\chi^2_{1,1} = 154.1528$, $\chi^2_{2,2} = 128.0843$, $\chi^2_{3,3} = 140.1684$, $\chi^2_{4,4} = 73.3749$, $p < 0.001$ respectively; BC50: $\chi^2_{1,1} = 12.4527$, $\chi^2_{2,2} = 27.6959$, $\chi^2_{3,3} = 21.1040$, $\chi^2_{4,4} = 19.4776$, $p < 0.001$ respectively). But we find no support for hypothesis H_{3b}. The Internet purchase of railway tickets is independent from contract cancellation for both BC25 and BC50 customers at any time ($p > .05$ for both segments in any year of contract).

Testing our hypotheses on pricing issues leads to a clear result: all hypotheses (H_{4x}) are fully supported. Price sensitivity plays a highly significant role for the cancellation context in any year of usage for BC25 customers (Pearson $\chi^2_{Discount\_i,Cancel\_j}$: $\chi^2_{1,1} = 24.9415$, $\chi^2_{2,2} = 154.8867$, $\chi^2_{3,3} = 113.3452$, $\chi^2_{4,4} = 76.3880$, $p < .001$ respectively). The same applies for the initial price and cancellation events, again for BC25 (Pearson $\chi^2_{Price\_1,Cancel\_j}$: $\chi^2_{1,1} = 1.1e+03$, $\chi^2_{1,2} = 453.6621$, $\chi^2_{1,3} = 173.5502$, $\chi^2_{1,4} = 1.5909$, $p < .05$ respectively) and BC50 ($\chi^2_{1,1} = 199.1376$, $\chi^2_{1,2} = 536.7368$, $\chi^2_{1,3} = 289.6997$, $\chi^2_{1,4} = 27.7737$, $p < .001$ respectively) customer segments. Analyzing the relationship between up-to-date standard price and cancellation over time, the initial price paid indeed seems to be a kind of reference point. For the BC25 customers, the price paid for ongoing contracts in any year of usage proves to be independent of customer cancellation when this price is below the price paid for the initial BahnCard (even at 0.1-level). Once the subsequent price exceeds the initial price of the BahnCard, we find a highly significant connection to customer cancellation (Pearson $\chi^2_{Price_i>Price1,Cancel\_i}$: $\chi^2_{2,2} = 399.8463$, $\chi^2_{3,3} = 181.3445$, $\chi^2_{4,4} = 158.3735$, $p < .001$). Latter also applies for the BC50 customers ($\chi^2_{2,2} = 630.9241$, $\chi^2_{3,3} = 329.5218$, $\chi^2_{4,4} = 184.5607$, $p < .001$), but the initial reference price seems to be less important: up to contract year three the current price also has an impact on cancellation ($\chi^2_{2,2} = 44.0675$, $\chi^2_{3,3} = 24.9745$, $p < .001$) when it is below the initial price. After that, time up-to-date prices cannot be associated to customer cancellation ($p > .5$).

Finally, the chi-square tests of independence reveal that the way of usage of a BahnCard, in terms of a rough categorization into suboptimal, beyond optimal and optimal, is associated with its cancellation (as intuitively expected). Particularly, the way of usage of the *current* BahnCard turns out to be connected to customer cancellation in any year of usage for both low- and high-prize contexts (BC25 (Pearson $\chi^2_{Usage\_i,Cancel\_i}$): $\chi^2_{1,1} = 16.8214$, $\chi^2_{2,2} = 232.5963$, $\chi^2_{3,3} = 154.3725$, $\chi^2_{4,4} = 81.7461$, $p < .001$ respectively; BC50: $\chi^2_{1,1} = 25.2781$, $\chi^2_{2,2} = 378.0743$, $\chi^2_{3,3} = 212.1321$, $\chi^2_{4,4} = 199.5003$, $p < .001$ respectively). Concerning *past* way of usage, this effect is mixed. Several elapsed contract periods exhibit statistically significant connections to cancellation events, but particularly early periods of relatively long contract durations do not ($p > 0.05$). Hence, the hypotheses H_{5a} and H_{5b} are fully supported.

5.3 Discussion

Study 2 connects learning, point of usage, price and way of usage to cancellations of customer loyalty programs. Cancellation rates are found to decrease over time. This should not only apply to the airline industry (Iliescu, Garrow, and Parker 2008) or the railway sector, but also be relevant in various sectors repeatedly dealing with customers, particularly in the context of other loyalty programs. Then, it is shown: Learning effects do have an impact on cancellation behavior and their influence decreases over time. Particularly, we find that customer learning fosters customer retention (in accordance with the findings of Iyengar, Ansari, and Gupta 2007), and complementary, unlearning facilitates the cancellation of customer loyalty programs, although latter effect holds only for the high-price context. At this, the significance of effects changes over time and (un-)learning affects cancellation more likely in '*early*' years of contract. This circumstance further signifies the relevance of (un-)learning effects in loyalty programs, and hence for customer retention and firm performance. Further, our findings concerning the point of usage have important consequences on the development and coordination of different distribution channels. In our case, the Internet purchase of railway tickets proves to be more advisable, since it cannot be associated to contract cancellations. This could imply that in the railway sector, online buyers are more loyal than counter customers. In this context, the implementation of appropriate pricing strategies for subsequent fees is found to be a crucial factor for controlling customer churn. The next study examines how the drivers of contract cancellation identified here contribute to cancellation of loyalty programs in low- and high-price contexts. Employing a sequential logistic regression model, we quantify corresponding (learning) effects and detect changes over time.

6. Study 3: Learning and Price Effects on Cancellation and Changes over Time

In studies 1 and 2, we focused on outlining the nature of collective (un-)learning curves in both low- and high-price contexts of customer loyalty programs, and illustrate the linkage of learning, usage and price issues to contract cancellation. In the following, we take a dynamical approach, analyzing (learning) effect changes over time. As Bingham and Davis (2012) develop a concept of learning sequences for organizational processes, they find that learning sequences exist and analyze their effects and evolution. Applying the idea of learning sequences to customer behavior, we assume that there might be several underlying learning processes throughout contract duration (e.g. experimental, trial-and-error, vicarious learning, learning from external advice) which add up to a learning sequence, and apart from changing contingent factors might justify effect changes over time: In study 2 we find that the influence of learning effects on cancellation changes through the different contract periods, particularly in different price contexts. We assume, that this could be coherent with a change of the direction of the effects, and thus formulate:

H_6: The direction of the influence of learning effects on loyalty card cancellation changes over time.

As shown in study 2, initial and current price affect the risk of cancellation in any year of contract. Referring to the concept of perceived price fairness (Bolton, Warlop, and Alba 2003; Xia, Monroe, and Cox 2004), we consider a constant direction of price effects, and eventually hypothesize:

H_7: The direction of the influence of initial and current price on loyalty card cancellation does not change over time.

To assess the impact of size and direction of effects we choose a rather technical approach, opening with the following question: Can a cancellation event simply be predicted on the basis of a relatively rough categorization of the current usage behavior, a customer's (in-)ability to learn how to use her loyalty card, and only a few information about demographics, price and point of usage? For each year of contract duration we employ a logistic regression model and determine and discuss the impact of price and learning. We detail these procedures in the next section.

6.1 Design and Procedure

We forecast cancellation events in the context described above, using a sequential logit model. Our aim is to quantify learn and price effects, and to identify changes of the direction of effects during contract duration in low- and high-price contexts. We re-employ the variables *usage*, *learn*, *sex*, *age*, *counter*, *discount* (BC25), *initial price* and *current price* (see also study 2) and arrange our dataset separately for each year of contract duration. For validation purposes we split our dataset into train and test data and then logistically regress on the cancellation events at the end of each BahnCard validity period in the contract duration, using the train data. Figure 13 depicts this procedure.

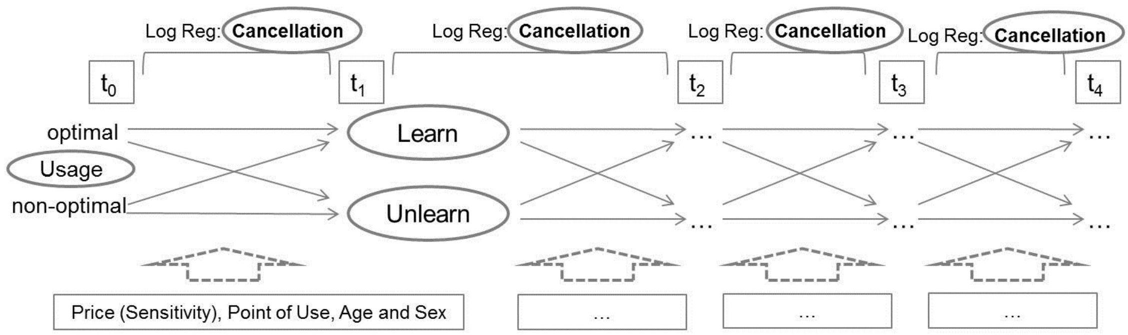


Figure 13. *Sequential Logit Model*

This sequence can be formalized with the following expressions:[17]

$$P(cancel\_t_i = 1) = \frac{1}{1+e^{-z_i}}\ , \tag{1}$$

where i defines the end of the respective contract year and

[17] This formula applies to both customer segments BC25 and BC50, but for latter $discount_i = 0$.

$$z_i = \beta_0 + \beta_1 * usage_i + \beta_2 * age_i + \beta_3 * sex + \beta_4 * counter_i + \beta_5 * discount_i + \beta_6 * price_i \qquad \text{(for } i = 1\text{).} \qquad (2)$$

$$z_i = \beta_0 + \beta_1 * usage_i + (\beta_2 * learn_1 + \cdots + \beta_i * learn_{i-1}) + \beta_{i+1} * age_i + \beta_{i+2} * sex + \beta_{i+3} * counter_i + \beta_{i+4} * discount_i + \beta_{i+5} * price_1 + \beta_{i+6} * price_i \qquad \text{(for } i > 1\text{).} \qquad (3)$$

Subsequently, we score the test dataset with the obtained parameter estimates to validate our model and to verify the appropriateness of this approach. The procedure is done for both the BC25 and BC50 customer segment.

6.2 Results

Examining the impact of learning (and unlearning) effects provides the following results: they do have an impact on contract cancellation (see also study 2), but effect directions and their significances vary over time, giving full support to hypothesis H_6. For example, in case of the BC25 customers unlearn exhibits a significant positive influence on cancellation in the first two years of contract duration (as it could be expected) but thereafter tends to decrease the probability of terminating the contract. Generally, unlearning effects seem to be relevant for cancellation events predominantly in the first contract period. Learning effects are less important. The corresponding direction of effect changes in early contract stages, but counter-intuitively tends to exhibit a positive impact on the cancellation probability in the low-price segment. In contrast, for the BC50 customers learning effects tend to decrease the probability of cancellation (as expected). In this segment, the unlearning effect also is significant in the first two years of contract duration. It is remarkable, that unlearning effects only contribute significantly to cancellation events in the last period of contract duration. At this, they always increase the cancellation risk. In summary, learning effects tend to foster long contract duration in the high-price context, whereas unlearning effects shorten it. In the low-price context, the direction of learning effects changes several times and tends to increase cancellation probabilities of contracts of more than two years length (which is counter-intuitive). Furthermore, unlearning effects positively impact cancellation probabilities in the first two years of contract, and then surprisingly decrease them.

Here, learning and unlearning effects seem to be more important in the first two years of contract duration, whereas in the high-price context only predominantly the last unlearning effects contribute to the cancellation events. In comparison of these two effects, unlearning effects seem to be of greater explanatory value in this context.

When it comes to explaining the impact of BahnCard prices on the contract cancellation, we find considerable differences between BC25 and BC50 customers. In both segments the current prize of any year of contract proves to have a statistically significant influence on the cancellation event, but for the low-prize segment we surprisingly find a negative impact on the cancellation probability, and in the high-price segment the current price increases it in each contract period. The initial is price also a relevant indicator in this context. It significantly decreases the probability of contract cancellation in both low- and high-price context (only exception is the first contract year in the BC50 segment, where the current and the initial price are the same).

Concerning the variable *usage*, the category describing suboptimal usage behavior proves to be statistically significant in the first three years of contract duration of BC25 customers. Among the BC50 customers this parameter contributes significantly in any year of contract duration towards an explanation of cancellation events. In both regimes it exhibits a positive effect on the cancellation probabilities. If a BahnCard is characterized by beyond optimal usage, this tends to reduce the risk of cancellation, although not always (BC25) or rather not (except 2nd year, BC50) significant.

The demographical information used in this application provide the following result: the customer's age significantly contributes to the explanation of contract cancellation in both low- and high-prize segments and in each year of contract duration. The rule is 'the younger, the higher the affinity to cancellation'. Sex only proves to significantly explain cancellation in the first three years of the BC25 customers, and in the 2nd and 4th of the contracts of BC50 customers. Generally, a male customer is less likely to cancel his contract.

In the BC25 customer segment we measured price sensitivity via the indicator variable discount, constituting whether a customer combined his BahnCard25 with any discounts or not. This variable comes out as statistically significant in predicting cancellation. Surprisingly, we obey a change of the direction of effects: hence, it positively affects the risk of cancellation in the first year, and thereafter the use of discounts decreases it. The same applies for counter activities: they significantly increase the probability of a contract cancellation in the first year of contract, and lowers it in the subsequent contract periods.

Full regression results for the respective years of contract duration are displayed in table 18-21 (BC25) and 22-25 (BC50).

Train Data

Predictor variable: Cancel1		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage1						
	Sub_opt ***	.2673795	.0485753	5.50	0.000	.1721737	.3625854
	Byo_opt ***	-.4704787	.0918828	-5.12	0.000	-.6505657	-.2903917
	Sex *	-.0940982	.0382737	-2.46	0.014	-.1691132	-.0190832
	Age ***	-.0197221	.0012541	-15.73	0.000	-.0221801	-.0172642
	Counter ***	.4978051	.0452635	11.00	0.000	.4090902	.58652
	Discount	.0608621	.043798	1.39	0.165	-.0249804	.1467047
	Price1 ***	-.0295995	.0018707	-15.82	0.000	-.0332659	-.025933
	_cons	.3276857	.1063901	3.08	0.002	.119165	.5362064

Number of obs = 20732 LR chi2(7) = 763.91 Prob > chi2 = 0.0000 Pseudo R2 = 0.1395

Test Data

Predictor variable: Cancel1		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Score1 ***	-5.298325	.4444654	-11.92	0.000	-6.169462	-4.427189
	_cons	2.763311	.3610806	7.65	0.000	2.055606	3.471016

Number of obs = 5192 LR chi2(1) = 142.09 Prob > chi2 = 0.0000 Pseudo R2 = 0.1296

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 18. *BC25: Logistic Regression Results Year 1*

Train Data

Predictor variable: Cancel2		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage2						
	Sub_opt ***	.5790542	.1213919	4.77	0.000	.3411304	.816978
	Byo_opt	-.2430255	.1635224	-1.49	0.137	-.5635235	.0774725
	Learn1						
	Learn	.1488668	.1439758	1.03	0.301	-.1333204	.4310541
	Unlearn ***	.2339516	.0655672	3.57	0.000	.1054422	.362461
	Sex †	-.1293224	.0472778	-2.74	0.006	-.2219853	-.0366595
	Age ***	-.0229216	.0015103	-15.18	0.000	-.0258817	-.0199615
	Counter ***	-.202611	.0580594	-3.49	0.000	-.3164053	-.0888167
	Discount ***	-.2548946	.0712091	-3.58	0.000	-.3944618	-.1153274
	Price1	-.0002564	.004578	-0.06	0.955	-.0092291	.0087163
	Price2 ***	-.2761223	.0191792	-14.40	0.000	-.3137129	-.2385317
	_cons	13.07305	1.103427	11.85	0.000	10.91037	15.23573

Number of obs = 14865 LR chi2(7) = 776.40 Prob > chi2 = 0.0000 Pseudo R2 = 0.1594

Test Data

Predictor variable: Cancel2		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Score2 ***	-7.539727	.5207613	-14.48	0.000	-8.5604	-6.519053
	_cons	4.675882	.4218643	11.08	0.000	3.849043	5.502721

Number of obs = 3721 LR chi2(1) = 220.23 Prob > chi2 = 0.0000 Pseudo R2 = 0.1627

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 19. *BC25: Logistic Regression Results Year 2*

Train Data

Predictor variable: Cancel3		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage3						
	Sub_opt *	.5126922	.2138309	2.40	0.017	.0935913	.931793
	Byo_opt †	-.5525483	.2871131	-1.92	0.054	-1.11528	.0101829
	Learn1						
	Learn	-.0916818	.171519	-0.53	0.593	-.4278529	.2444892
	Unlearn **	.2923039	.095267	3.07	0.002	.1055841	.4790238
	Learn2						
	Learn	-.302301	.2571228	-1.18	0.240	-.8062524	.2016503
	Unlearn †	.1938775	.143792	1.35	0.078	-.0879496	.4757045
	Sex *	-.1449627	.065908	-2.20	0.028	-.27414	-.0157854
	Age ***	-.0211077	.0020914	-10.09	0.000	-.0252069	-.0170086
	Counter ***	-.3804803	.0874149	-4.35	0.000	-.5518104	-.2091503
	Discount *	-.2698443	.1097479	-2.46	0.014	-.4849463	-.0547424
	Price1 ***	-.0321867	.0076579	-4.20	0.000	-.0471959	-.0171775
	Price3 ***	-.2733622	.0297071	-9.20	0.000	-.331587	-.2151374
	_cons	14.45308	1.813562	-9.20	0.000	10.89857	18.0076

Number of obs = 9758 LR chi2(7) = 414.49 Prob > chi2 = 0.0000 Pseudo R2 = 0.1582

Test Data [Continued]

Predictor variable: Cancel3		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Score3 ***	-8.358625	.9051236	-9.23	0.000	-10.13263	-6.584616
	_cons	5.28122	.7758297	6.81	0.000	3.760622	6.801818
	Number of obs = 2383 LR chi2(1) = 85.93 Prob > chi2 = 0.0000 Pseudo R2 = 0.1486						

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 20. *BC25: Logistic Regression Results Year 3*

Train Data

Predictor variable: Cancel4		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage4						
	Sub_opt **	1.07016	.3754394	2.85	0.004	.3343122	1.806008
	Byo_opt	.2507131	.4378062	0.57	0.567	-.6073714	1.108798
	Learn1						
	Learn *	-.3515801	.2374953	-1.48	0.039	-.8170623	.1139021
	Unlearn	.0009643	.1340184	0.01	0.994	-.2617069	.2636355
	Learn2						
	Learn	.0742739	.3166385	0.23	0.815	-.5463262	.694874
	Unlearn	.2346243	.1889822	1.24	0.214	-.135774	.6050226
	Learn3						
	Learn †	.7694433	.4031464	1.91	0.056	-.0207092	1.559596
	Unlearn	-.1653782	.2818142	-0.59	0.557	-.7177239	.3869676
	Sex †	.1435939	.0850454	1.69	0.091	-.0230919	.3102797
	Age ***	-.0203129	.0027098	-7.50	0.000	-.0256241	-.0150017
	Counter **	-.3127357	.1191712	-2.62	0.009	-.5463071	-.0791644
	Discount ***	-.5157693	.1493044	-3.45	0.001	-.8084005	-.2231381
	Price1 ***	-.0544689	.0102242	-5.33	0.000	-.0745079	-.0344298
	Price4 ***	-.5623422	.0561347	-10.02	0.000	-.6723641	-.4523202
	_cons	30.16949	3.278696	9.20	0.000	23.74336	36.59561
	Number of obs = 6797 LR chi2(7) = 305.60 Prob > chi2 = 0.0000 Pseudo R2 = 0.1702						

Test Data

Predictor variable: Cancel4		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1							
	Score4 ***	-8.782198	1.173456	-7.48	0.000	-11.08213	-6.482267
	_cons	5.64092	1.029995	5.48	0.000	3.622166	7.659673
	Number of obs = 1672 LR chi2(1) = 54.61 Prob > chi2 = 0.0000 Pseudo R2 = 0.1493						

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 21. *BC25: Logistic Regression Results Year 4*

Train Data

Predictor variable: Cancel1		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage1						
	Sub_opt ***	.4756355	.0374122	12.71	0.000	.4023089	.5489621
	Byo_opt	-.7668171	.531948	-1.44	0.149	-1.809416	.2757818
	Sex ***	-.1374213	.0331062	-4.15	0.000	-.2023083	-.0725343
	Age ***	-.0239629	.0009613	-24.93	0.000	-.025847	-.0220787
	Counter ***	.5254999	.0382934	13.72	0.000	.4504462	.6005536
	Price1 ***	.0018916	.0003343	5.66	0.000	.0012363	.0025468
	_cons	-1.169138	.0650967	-17.96	0.000	-1.296725	-1.041551

Number of obs = 22319 LR chi2(7) = 933.98 Prob > chi2 = 0.0000 Pseudo R2 = 0.1386

Test Data

Predictor variable: Cancel1		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Score1 ***	-5.494056	.3921509	-14.01	0.000	-6.262657	-4.725454
	_cons	3.013052	.296428	10.16	0.000	2.432064	3.59404

Number of obs = 5589 LR chi2(1) = 206.82 Prob > chi2 = 0.0000 Pseudo R2 = 0.1338

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 22. *BC50: Logistic Regression Results Year 1*

Train Data

Predictor variable: Cancel2		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage2						
	Sub_opt ***	.7431805	.0659105	11.28	0.000	.6139982	.8723628
	Byo_opt *	-1.607647	.7238119	-2.22	0.026	-3.026292	-.1890019
	Learn1						
	Learn	-.0898962	.0990393	-0.91	0.364	-.2840097	.1042173
	Unlearn ***	.3693834	.055955	6.60	0.000	.2597136	.4790533
	Sex	.0248277	.0429621	0.58	0.563	-.0593765	.1090319
	Age ***	-.019732	.0011794	-16.73	0.000	-.0220436	-.0174204
	Counter *	-.1250003	.0495949	-2.52	0.012	-.2222045	-.0277962
	Price1 ***	-.0048165	.0010069	-4.78	0.000	-.0067901	-.002843
	Price2 ***	.0058672	.0009812	5.98	0.000	.0039441	.0077903
	_cons	-1.500894	.0927014	-16.19	0.000	-1.682586	-1.319203

Number of obs = 16759 LR chi2(7) = 802.92 Prob > chi2 = 0.0000 Pseudo R2 = 0.1521

Test Data [Continued]

Predictor variable: Cancel2		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Score2 ***	-6.29703	.484187	-13.01	0.000	-7.246019	-5.348041
	_cons	3.58395	.391392	9.16	0.000	2.816836	4.351065

Number of obs = 4156 LR chi2(1) = 172.08 Prob > chi2 = 0.0000 Pseudo R2 = 0.1448

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 23. *BC50: Logistic Regression Results Year 2*

Train Data

Predictor variable: Cancel3		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage3						
	Sub_opt ***	.7188157	.1030873	6.97	0.000	.5167684	.920863
	Byo_opt	-.6704568	.7370258	-0.91	0.363	-2.115001	.7740872
	Learn1						
	Learn	-.1371264	.1152719	-1.19	0.234	-.3630553	.0888024
	Unlearn **	.2679592	.0935053	2.87	0.004	.0846922	.4512263
	Learn2						
	Learn	-.2179856	.1568131	-1.39	0.164	-.5253335	.0893624
	Unlearn ***	.5422147	.0957284	5.66	0.000	.3545905	.7298389
	Sex	-.0972741	.0612856	-1.59	0.112	-.2173917	.0228434
	Age ***	-.0222946	.0016085	-13.86	0.000	-.0254473	-.0191419
	Counter †	-.1423367	.0731626	-1.95	0.052	-.2857329	.0010594
	Price1 ***	-.0044596	.0013008	-3.43	0.001	-.0070091	-.0019102
	Price3 **	.0036534	.0012311	2.97	0.003	.0012405	.0060663
	_cons	-1.306495	.1380299	-9.47	0.000	-1.577028	-1.035961

Number of obs = 10103 LR chi2(7) = 497.34 Prob > chi2 = 0.0000 Pseudo R2 = 0.1615

Test Data

Predictor variable: Cancel3		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1							
	Score3 ***	-6.194752	.6689345	-9.26	0.000	-7.505839	-4.883664
	_cons	3.416759	.5622968	6.08	0.000	2.314678	4.51884

Number of obs = 2524 LR chi2(1) = 83.22 Prob > chi2 = 0.0000 Pseudo R2 = 0.1415

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 24. *BC50: Logistic Regression Results Year 3*

Train Data

Predictor variable: Cancel4		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1	Usage4						
	Sub_opt ***	1.017672	.1562682	6.51	0.000	.711392	1.323952
	Byo_opt	-.6089508	1.039108	-0.59	0.558	-2.645565	1.427663
	Learn1						
	Learn	.1201663	.1561639	0.77	0.442	-.1859093	.4262418
	Unlearn	.0916433	.1339734	0.68	0.494	-.1709397	.3542264
	Learn2						
	Learn	-.0857325	.184297	-0.47	0.642	-.4469481	.2754831
	Unlearn	.2061346	.1465425	1.41	0.160	-.0810834	.4933525
	Learn3						
	Learn	-.1274749	.2369625	-0.54	0.591	-.5919129	.336963
	Unlearn †	.1698037	.1505395	1.13	0.059	-.1252483	.4648557
	Sex **	-.212289	.0821682	-2.58	0.010	-.3733356	-.0512423
	Age ***	-.0108393	.0020326	-5.33	0.000	-.0148231	-.0068554
	Counter ***	-.3438612	.1003146	-3.43	0.001	-.5404743	-.1472482
	Price1 ***	-.0067795	.0015135	-4.48	0.000	-.009746	-.0038131
	Price4 ***	.0053729	.0014224	3.78	0.000	.0025852	.0081607
	_cons	-1.842428	.2147087	-8.5	0.000	-2.263249	-1.421606
	Number of obs = 6075 LR chi2(7) = 273.62 Prob > chi2 = 0.0000 Pseudo R2 = 0.1579						

Test Data

Predictor variable: Cancel4		Coef.	Std. Err.	Z	P>|Z|	[95% Conf.	Interval]
0		(base outcome)					
1							
	Score4 ***	-8.174239	1.141897	-7.16	0.000	-10.41232	-5.936163
	_cons	5.04223	.967529	5.21	0.000	3.145908	6.938552
	Number of obs = 1480 LR chi2(1) = 52.32 Prob > chi2 = 0.0000 Pseudo R2 = 0.1476						

*** p≤0.001, ** 0.001<p≤0.01, * 0.01<p≤0.05, † 0.05<p≤0.10

Table 25. *BC50: Logistic Regression Results Year 4*

6.3 Discussion

At this juncture, we do not focus on the development of a prediction model for cancellations, as for example famously done by Coussement and Van den Poel (2008), Hadden et al. (2007) or Neslin et al. (2006), although our model obviously outperforms random models. This approach is supposed to illustrate the impact of learning and basic customer information on cancellation behavior, the interdependency with the intensity or quality of usage, and pricing issues and their changes over time. It complements the findings of study 1 and 2, and outlines temporal effects in terms of usage, learning and pricing (price perception) in a cancellation context. We find that unlearning effects tend to increase contract cancellation probabilities in the high-price context, whereas learning effects tend to lower cancellation risks. Counter-intuitively learning tends to make cancellations more likely in contracts of more than two years in the low-price segment (within the first two years of contract duration those effects are mixed). Unlearning fosters cancellation in the first two years of a contract, and surprisingly tends to reduce the cancellation risks afterwards. These observations concerning the low-price segment seem to be irrational. The low price of the BahnCard indicates that it is less important for the way of usage whether a customer learns, unlearns or neither learns nor unlearns. Still, the question remains why the impact of learning (and unlearning) on cancellation exhibits unexpected effects in the first two years of a contract (and from contract year three)? Learning theories suggest that decision makers' patterns of learning and action depend on the extent to which their organizations' performance differs from their aspiration levels (Cyert and March 1963; Greve 2003). Aspiration-performance feedback models emphasize how perceptions of success and failure motivate change: satisfactory outcomes that meet aspirations foster local search of old certainties that reinforce and refine lessons drawn from earlier experience; outcomes that fail to meet or exceed aspirations stimulate nonlocal search for new possibilities to correct or further enhance performance (Cyert and March 1963; Levitt and March 1988; March and Shapira 1992). We assume that a certain level of price induces rational behavior. Below this, other (contingent) factors seem to be of greater importance.

Another interesting outcome is the following: the higher the subsequent prices of ongoing annual contracts, the lower is the risk of a contract cancellation in the low- price segment, and the higher the corresponding risk in the high-price segment. This finding has important implications on the pricing of two-part tariff systems. Accordingly, the company implementing loyalty cards based on a two-part tariff-system should set the initial prices relatively high and in the following contract periods reduce it in the high-price segment, and increase it in the low-price segment.

7. General Discussion

This study's purpose is to shed light on the nature of customers' learning and unlearning curves and point out linkages between learn and price effects and customer retention (in general as well as concerning change over time). Table 26 summarizes the main findings.

Learning and unlearning of loyalty card usage in two-part pricing system is not characterized by an inverse relationship but substantially involves the price context (Study 1). From firm perspective, learning and unlearning, as well as point of usage and pricing issues can be significantly associated with contract cancellation in loyalty programs (Study 2). Knowledge on effect changes over time and variations on the price context (Study 3) can be used by firms to redevelop, communicate and fine-tune their loyalty card systems. Thus, understanding the nature of (un)learning and its interrelationship with pricing issues contribute to a successful employment of loyalty programs.

Field		Hypothesis	Result	Addendum to Findings
Learning Curve	H1a	Curve structures differ (learn vs. unlearn).	✓	In low- and high-price context.
	H1b	Curve structures vary across price contexts.	✓	–
Learning (and Cancellation)	H2a	Cancellation rate decreases over time.	✓	In low- and high-price context.
	H2b	Cancellation rate is lower for learners and higher for 'unlearners'.	Partly confirmed	Full support in the high- and mixed support in the low-price context.
	H2c	(Un)Learning effects affect cancellation.	✓	But: not regardless when (during the customer life cycle) and how (learn, unlearn) they appear.
PoU (and Cancellation)	H3a	Ticket purchases via counter affect cancellation.	✓	In low- and high-price context.
	H3b	Ticket purchases via Internet affect cancellation.	Rejected	No support in low- and high-price context.
Price (and Cancellation)	H4a	Price sensitivity affects cancellation.	✓	In low- and high-price context.
	H4b	Initial price affects cancellation.	✓	In low- and high-price context.
	H4c	Current price affects cancellation.	✓	In low- and high-price context.
Usage (and Cancellation)	H5a	Current usage affects cancellation.	✓	In low- and high-price context.
	H5b	Past usage can affect cancellation.	Partly confirmed	In low- and high-price context, but not in any period.
Learning Effect	H6	Effect direction changes over time.	✓	Effect direction varies across low- and high-price context.
Price Effect	H7	Effect direction does not change over time.	✓	Effect direction is constant across low- and high-price context.

Table 26. *Summary of Results*

7.1 Theoretical Implications

This research adds to theory how customers learn in loyalty programs, and how behavioral aspects and price structures affect customer loyalty. Analyzing customer data of a satellite television firm, Jamal and Bucklin (2006) find significant links between churn rates and variables capturing customer service experience, failure recovery efforts, and payment equity. Our results extend their finding concerning service experience in terms of usage, learning and unlearning to the railway sector, which are relevant most likely in various other customer loyalty program contexts, particularly in two-part tariff systems.

The present work likewise complements a recent literature on choice and consumption under multi (two and more)-part tariffs (Ascarza, Lambrecht, and Vilcassim 2012; Bagh and Bhargava 2007; Grubb 2009; Grubb and Osborne 2011; Iyengar, Ansari, and Gupta 2007; Jensen 2006), which has so far abstracted from potential effects of the tariff structure on usage and customer retention. As an exception, Iyengar et al. (2011) explore how tariff structure affects customer retention, usage and profitability of access services on pay-per-use versus two-part tariffs, and find that customers' marginal utility of consumption is lower on latter tariff. We integrate customer learning and unlearning into this context and highlight their temporal effects in a longitudinal approach. More broadly our work contributes to research that explores behavioral effects of pricing and customer relationship management (CRM). This includes the insight that attributes of a price or a tariff structure can affect behavior beyond their direct cost implications (Bertini and Wathieu 2008), systematic effects of price endings on customers' purchase decisions (Anderson and Simester 2003; Thomas and Morwitz 2005), or contractual change (particularly termination) that follows specific price adjustments (Study 2). Analyzing methodological factors in the contribution to the accuracy of customer churn predictive models Neslin et al. (2006) find that logistic approaches perform "relatively well". However, they can also help to determine the importance and direction of learn and price effects over time within a tariff system (Study 3). Eventually, the definition of customer learning in this paper is categorized in terms of change in rational decision making and supplements conventional economic learning concepts (of product usage). Still, in learning curve research the role of organizational (Baum and Dahlin

2007) as well as behavioral performance (in terms of contractual behavior) is implicit (Study 1). So our approach demonstrates the role of learning on loyalty program performance.

Past research in psychology and marketing suggests that the pricing structure a firm chooses can alter customers' value for a product or a service (Iyengar et al. 2011). Our results motivate a more extensive study of how different tariff structures (e.g., three-part tariffs and flat fee pricing), customer learning and usage adaption affect the stability of customer contracts. For example, future research could examine the effect of other tariff structures, such as bucket pricing that strictly limit consumption to the usage allowance (Schlereth and Skiera 2012), on customers' valuation of a service and their willingness to adopt and change tariffs. Future work could also address customer acquisition and market expansion effects of introducing two- or more-part tariffs and could examine how a firm can optimally combine different tariff systems. Besides, an examination of the validity and robustness of this approach including other products and service industries (at later stages in the life-cycle that operate in a competitive environment) seems promising.

Of course, our analysis does not come without limitations. For example, we did not control for income effects, nor did we consider the possibility to switch between tariff regimes. A comprehensive (multi-stage) approach which integrates the competing risks of upgrade or downgrade scenarios as well as switching costs could also be an interesting issue for future research. Although data from CRM databases are more realistic, they suffer from consumer self-selection issues and limited variability in prices over time as compared to field experiment data (Iyengar et al. 2011). Finally, we considered a huge customer loyalty program offered by the major German railway company.

7.2 Managerial Implications

An emerging question is how firms should make marketing mix choices when customers exhibit various types of bounds on rationality. As Ellison (2005) notes, if customers exhibit various biases relative to rational choice, from the firm's point of view, such biases will have the same practical importance as product differentiation, though an identical product might be differentiated by idiosyncrasies in consumer cognition rather than in tastes. This study suggest a possibility to model adaption of usage and learning in order to appropriately re-develop and optimize operative tariff-systems.

Our findings have important implications. First, they suggest that companies should make use of CRM databases for assessing the impact of (new) tariff structures, and hence to better understand how (new) tariffs affect customer behavior. This is important to set optimal prices (and switching fees) and implement segment-specific approaches and adequate CRM-strategies. Thereby, our approach considers the concept of perceived price fairness (Bolton, Warlop, and Alba 2003; Xia, Monroe, and Cox 2004), at this, the result being consistent with prospect theory and mental accounting, which suggests that consumers tend to perceive multiple prices as more punishing than a single price of equal amount (Kahneman and Tversky 1979; Thaler 1985; Thaler and Johnson 1990) – in our case, not least when the subsequent prices exceed the initial price. Additionally, these specific aspects of customer knowledge are applicable for the composition and configuration of customer loyalty programs. Second, they outline the importance of customer learning in loyalty card systems as a driver of customer retention and emphasize the need to conceptualize and foster learning by providing transparency and support in company communications, incentives to learn, and other motivational aspects in customer relationships. Third, they add to existing issues in e-tailing research (Grewal and Levy 2009) pointing on how to coordinate online and offline distribution channels in the context of two-part pricing systems. Here, Wallace, Giese, and Johnson (2004) conclude that multiple channel strategies are useful in satisfying multiple channel customers' high expectations and retaining customers. However, our results provide explicit indication for differences in loyalty in different distribution channels of the railway setting and can help to develop preliminary concepts and strategies to approach this issue.

Altogether, our findings emphasize the relevance for an integrative treatment of usage, usage adoption (learning), and perceptional price policies and strategies in the development and application of CRM strategies and concepts.

8. References

Anderson, Eric, and Duncan Simester (2003). Effect of $9 price endings on retail sales: Evidence from field experiments. *Quantitative Marketing and Economics*, 1(1), 93–110.

Argote, Linda (1999). *Organizational learning: Creating, retaining and transferring knowledge*. Norwell, MA: Kluwer Academic.

Argyris, Chris (1999). *On organizational learning*. Oxford, UK: Blackwell Publishers Ltd.

Ascarza, Eva, Anja Lambrecht, and Naufel Vilcassim (2012). When talk is “free”: The effect of tariff structure on usage under two- and three-part tariffs. *Journal of Marketing Research*, 49(6), 882–899.

Babutsidze, Zakaria (2011). Returns to product promotion when consumers are learning how to consume. *Journal of Evolutionary Economics*, 21(5), 783–801.

Bagh, Adib, and Hemant K. Bhargava (2007). *Doing more with less: Price discrimination with three-part vs. two-part tariffs*. Davis, CA: University of California.

Baum, Joel A. C., and Kristina B. Dahlin (2007). Aspiration performance and railroad’s patterns of learning from train wrecks and crashes. *Organization Science*, 18(3), 368–385.

Bertini, Marco, and Luc Wathieu (2008). Research note - Attention arousal through price partitioning. *Marketing Science*, 27(2), 236–46.

Bingham, Christopher B., and Jason P. Davis (2012). Learning sequences: Their existence, effect, and evolution. *Academy of Management Journal*, 55(3), 611–641.

Bolton, Lisa E., Luk Warlop, and Joseph W. Alba (2003). Consumer perceptions of price (un)fairness. *Journal of Consumer Research*, 29(4), 474–491.

Brown, John S., and Paul Duguid (1991). Organizational learning and communities-of-practice: Toward a unified view of working, learning, and innovation. *Organization Science*, 2(1), 40–57.

Choi, Duke H., Shul M. Kim, Sang-Il Kim, and Soung H. Kim (2006). Customer loyalty and disloyalty in internet retail stores: Its antecedents and its effect on customer price sensitivity. *International Journal of Management*, 23(4), 925–941.

Chuang, You-Ta, and Joel A. C. Baum (2003). It's all in the name: Failure-induced learning by multiunit change. *Administrative Science Quarterly*, 48(1), 33–59.

Churchill, Gilbert A. Jr., and George P. Moschis (1979). Television and interpersonal influences on adolescent consumer learning. *Journal of Consumer Research*, 6(1), 23–35.

Coussement, Kristof, and Dirk Van den Poel (2008). Churn prediction in subscription services: An application of support vector machines while comparing two-parameter selection techniques. *Expert Systems with Applications*, 34(1), 313–327.

Cyert, Richard M., and James G. March (1963). *A behavioral theory of the firm*. Englewood Cliffs, NJ: Prentice Hall.

Dahl, Darren W., and C. Page Moreau (2007). Thinking inside the box: Why consumers enjoy constrained creative experiences. *Journal of Marketing Research*, 44(3), 357–369.

DellaVigna, Stefano, and Ulrike Malmendier (2006). Paying not to go to the gym. *American Economic Review*, 96(3), 694–719.

Denrell, Jerker (2003). Vicarious learning, undersampling of failure, and the myths of management. *Organization Science*, 14(3), 227–243.

Ellison, Glenn (2005). Bounded rationality in industrial organization. Paper presented at the 2005 *Econometric Society World Congress*, University College London (August 19–24).

Goettler, Ronald L., and Karen Clay (2011). Tariff choice with consumer learning and switching costs. *Journal of Marketing Research*, 48(4), 633-652.

Greve, Henrich R. (2003). *Organizational learning from performance feedback: A behavioral perspective on innovation and change*. Cambridge: Cambridge University Press.

Grewal, Dhruv, and Michael Levy (2009). Emerging issues in retailing research. *Journal of Retailing*, 85(4), 522-526.

Grubb, Michael D. (2009). Selling to overconfident consumers. *American Economic Review*, 99(5), 1770–1807.

Grubb, Michael D., and Matthew Osborne (2011). Tariff choice, usage uncertainty, biased beliefs, and learning. SLOAN School of Management, MIT: Working paper.

Hadden, John, Ashutosh Tiwari, Rajkumar Roy, and Dymitr Ruta (2007). Computer-assisted customer churn management: State-of-the-art and future trends. *Computers & Operations Research*, 34(10), 2902–2917.

Haunschild, Pamela R., and Mooweon Rhee (2004). The role of volition in organizational learning: The case of automotive product recalls. *Management Science*, 50(11), 1545–1560.

Haunschild, Pamela R., and Bilian N. Sullivan (2002). Learning from complexity: Effects from accident/incident heterogeneity on airline learning. *Administrative Science Quarterly*, 47(4), 609–643.

Hennig-Thurau, Thorsten, and Alexander Klee (1997). The impact of customer satisfaction and relationship quality on customer retention: A critical reassessment and model development. *Psychology & Marketing*, 14(8), 737–764.

Huber, George P. (1991). Organizational learning: The contributing process and the literatures. *Organization Science*, 2(1), 88–115.

Iliescu, Dan C., Laurie A. Garrow, and Roger A. Parker (2008). A hazard model of US airline passengers' refund and exchange behavior. *Transportation Research Part B: Methodological*, 42(3), 229–242.

Iyengar, Raghuram, Asiim Ansari, and Sunil Gupta (2007). A model of consumer learning for service quality and usage. *Journal of Marketing Research*, 44(4), 529–544.

Iyengar, Raghuram, Kamel Jedidi, Skander Essegaier, and Peter J. Danaher (2011). The impact of tariff structure on customer retention, usage, and profitability of access services. *Marketing Science*, 30(5), 820–836.

Jamal, Zainab, and Randolph E. Bucklin (2006). Improving the diagnosis and prediction of customer churn: A heterogeneous hazard modeling approach. *Journal of Interactive Marketing*, 20(3-4), 16–29.

Jensen, Sissel (2006). Implementation of competitive nonlinear pricing: Tariffs with inclusive consumption. *Review of Economic Design*, 10(1), 9–29.

Kahneman, Daniel, and Amos Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 163–191.

Kim, Ji-Yub (2000). *Crash test without dummies: A longitudinal study of interorganizational learning from failure experience in the U.S. commercial banking industry, 1984–1998*. Unpublished Ph.D. dissertation, University of Wisconsin-Madison, Madison, WI.

Kotler, Philip (1994). *Marketing management. Analysis, planning, implementation, and control*. Englewood Cliffs, NJ: Prentice Hall.

Lakshmanan, Arun, and H. Shanker Krishnan (2011). The aha! experience: Insight and discontinuous learning in product usage. *Journal of Marketing*, 75(6), 105–123.

Lambrecht, Anja, and Bernd Skiera (2006). Paying too much and being happy about it: existence, causes and consequences of tariff-choice biases. *Journal of Marketing Research*, 43(2), 212–23.

Levav, Jonathan, Ran Kivetz, and Cecile K. Cho (2010). Motivational Compatibility and Choice Conflict. *Journal of Consumer Research*, 37(3), 429–442.

Levitt, Barbara, and James G. March (1988). Organizational learning. *Annual Review of Sociology*, 14, 319–40.

March, James G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1), 71–87.

March, James G., and Zur Shapira (1992). Variable risk preferences and the focus of attention. *Psychological Review*, 99(1), 172–183.

Miner, Anne S., Paula Bassoff, and Christine Moorman (2001). Organizational improvisation and learning: A field study. *Administrative Science Quarterly*, 46(2), 304–337.

Miner, Anne S., Ji-Yub Kim, Ingo Holzinger, and Pamela Haunschild (1999). Fruits of failure: Organizational level failure and population level learning, in: Anne S. Miner and Philip Anderson (eds.), *Advances in strategic management, Vol. 16: Population level learning and industry change*, Stamford, CT: JAI Press, 187–220.

Miravete, Eugenio J. (2002). Choosing the wrong calling plan? Ignorance and learning. *American Economic Review*, 93(1), 297–310.

Moreau, C. Page, and Darren W. Dahl (2005). Designing the solution: The influence of constraints on consumer creativity. *Journal of Consumer Research*, 32(1), 13–22.

Moschis, George P., and Gilbert A. Churchill Jr. (1978). Consumer socialization: A theoretical and empirical analysis. *Journal of Marketing Research*, 15(4), 599–609.

Narayanan, Sridhar, Pradeep K. Chintagunta, and Eugenio J. Miravete (2007). The role of self selection, usage uncertainty and learning in the demand for local telephone service. *Quantitative Marketing and Economics*, 5(1), 1–34.

Neslin, Scott A., Sunil Gupta, Wagner Kamakura, Junxiang Lu, and Charlotte H. Mason (2006). Defection detection: Measuring and understanding the predictive accuracy of customer churn models. *Journal of Marketing Research*, 43(2), 204–211.

Nunes, Joseph C. (2000). A cognitive model of people's usage estimations. *Journal of Marketing Research*, 37(4), 397–409.

Robertson, Thomas S., and Hubert Gatignon (1986). Competitive effects on technology diffusion. *Journal of Marketing Research*, 50(3), 1–12.

Schlereth Christian, and Bernd Skiera (2012). Measurement of consumer preferences for bucket pricing plans with different service attribute. *International Journal of Research in Marketing*, 29(2), 167–180.

Schmale, Hendrik, Thomas Ehrmann, and Alexander Dilger (2013). Buying without using – Biases of German BahnCard buyers. *Applied Economics*, 45(7), 933–941.

Shih, Chuan-Fong, and Alladi Venkatesh (2004). Beyond adoption: Development and application of a use-diffusion model. *Journal of Marketing*, 68(1), 59–72.

Squire, Larry R. (1986). Mechanisms of memory. *Science*, 232(4758), 1612–1619.

Thaler, Richard H. (1985). Mental accounting and consumer choice. *Marketing Science*, 4(3), 199–214.

Thaler, Richard H. (1999). Mental accounting matters. *Journal of Behavioral Decision Making*, 12(3), 183–206.

Thaler, Richard H., and Eric J. Johnson (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, 36(6), 643–660.

Thomas, Manoj, and Vicky Morwitz (2005). Penny wise and pound foolish: The left-digit effect in price cognition. *Journal of Consumer Research*, 32(1), 54–64.

Van Osselaer, Stijn M. J., and Chris Janiszewski (2001). Two ways of learning brand associations. *Journal of Consumer Research*, 28(2), 202–223.

Wallace, David W., Joan L. Giese, and Jean L. Johnson (2004). Customer retailer loyalty in the context of multiple channel strategies. *Journal of Retailing*, 80(4), 249–263.

Ward, Scott (1974). Consumer socialization. *Journal of Consumer Research*, 1(2), 1–14.

Xia, Lan, Kent B. Monroe, and Jennifer L. Cox (2004). The price is unfair! A conceptual framework of price fairness perceptions. *Journal of Marketing*, 68(4), 1–15.

IV. THE SUCCESS OF ART GALLERIES: A DYNAMIC MODEL WITH COMPETITION AND INFORMATION EFFECTS

"We have art to save ourselves from the truth."
Friedrich Nietzsche (1844-1900)

1. Abstract

An intrinsic characteristic of cultural goods is the unpredictability of their economic success. Arts goods in particular share characteristics with credence, inspection and experience goods. Accordingly, art collectors rely on the experience and the reputation of art galleries when investing in artwork. Some qualitative sociological studies have found that only a few very successful galleries represent the bulk of the most visible and most successful artists (e.g. Crane 1989; Currid 2007). This paper investigates the success of art galleries in a dynamic model which elaborates different statistical processes that allow us to analyze the development of different types of success distributions in the market for art galleries. Instead of applying standard economic analysis only, we employ methods form statistical physics to construct a model of gallery investment and competition. Our model entails information, competition and innovation effects. Subsequently, art market data are used to test which version of the model fits best. We find the lognormal distribution provides the best fit and conclude that the data generating process is compatible with the version of the model which entails an inhomogeneous geometric Brownian motion. Hence the success of art galleries depends strongly on information and innovation effects, but is hardly affected by competition effects. We argue that the superstar effect in the case of art galleries can be understood as an appropriation of *search and entrance costs* which emerge whenever consumption requires special knowledge and social inclusion.

2. Introduction

From an economic perspective, the art market (in a 'nutshell') displays the pivotal problems of markets with high quality uncertainty and considerable innovation intensity. New artists entering the market are unknown and the products they manufacture require a lot of explanation and evaluation. On the other side of the market, collectors and investors know neither the artist nor her or his work. It is the task of galleries to close the gap between artists and collectors/investors. Entering the market of galleries is also a highly risky enterprise since it entails specific investments, particularly in knowledge of arts, i.e., human capital. This specific human capital does not command high returns outside galleries (and museums). Moreover, with established galleries already in the market, it is difficult to establish a new gallery as a newcomer. This structure of the market seems to be well suited for an investigation of its evolutionary dynamics. First of all, the market is clearly defined and separated from other markets as, e.g., the secondary market for known art work. Moreover, 'success' in this market is easily observed by the ranking of new artists, introduced by the respective gallery. Although galleries are certainly not in the main interest of economics, we believe they may serve as a model-market for intermediaries in markets with high quality uncertainty and innovation. That is why we consider it well suited for an application of our methodology which can presumably be transferred to similar markets.

To understand art markets in greater detail, it is to be recognized that an intrinsic characteristic of cultural goods is the unpredictability of their economic success. Arts goods share characteristics with credence, inspection and experience goods. These characteristics create problems for uninformed customers because of the uncertainty about quality that goes hand in hand with artworks. Additionally, it is obvious that art is taste-driven and thus needs an intense, subjective evaluation. A buyer therefore has to overcome this information problem that is inherent in the characteristics of works of art. Some of the studies which examine the evaluation of cultural goods are discussed by Frey (1997), Ginsburgh (2003) as well as Hutter and Throsby (2008). Reputational approaches in this context are provided by Canals-Cerdá (2012) and Schönfeld and Reinstaller (2007).

Uncertain subjective quality evaluations trigger the emergence of institutions in a market economy intended to reduce this uncertainty. Referring to this fact, a whole industry of experts has evolved, which helps to overcome quality uncertainty by actively evaluating and distributing information on works of art (Becker 1982; Caves 2000; Currid 2007). Particularly gallery owners like Monika Sprüth have become very important because they decide which artists they will show, which works they will present and how much they will invest in the development of the artist and the style she or he represents.

In a world centered on stardom and hits we assume that the glamorous business of arts should not only have superstars on the side of artists, but also winners on the side of galleries. Some qualitative sociological studies have found that only a few very successful galleries represent the bulk of the most visible and most successful artists (e.g. Crane 1989; Currid 2007). Nevertheless, despite the fact that the superstar effects are analyzed in mass markets (e.g. Franck and Nüesch 2007), deep-pocket markets like the market for art galleries are still hardly ever explored. Heretofore, researchers have paid more attention to the economics of museums. For instance, Camarero, Garrido, and Vicente (2011) provide empirical evidence on innovations in museums and their impact on museums' economic, market and social performance, whereas Frey and Meier (2006) reflect upon the functioning of museums in general, and particularly address the evolution of 'superstar museums'. Moreover, Frey (1998) investigates the impact of superstar status of museums on museum policy and its consequences for human resource management.

In this context, Adler's (1985) and Rosen's (1981) theories of superstars have been applied to various markets. Ehrmann et al. (2009), for instance, analyze *superstar effects* in the market for quality restaurants, Walls (2010) analyzes weekly DVD sales revenues in North-America, Pitt (2010) emphasizes a new understanding of the music industry from a performing rights organization, Filimon et al. (2011) explore stardom and popularity of musical artists in Spain concerning their purchase of CDs, and Nelson and Glotfelty (2012) examine the relationship between movie star power and box office revenues.

In this paper, we examine the success of galleries in the German art market. For instance, when Monika Sprüth opened her first gallery in Cologne in February 1983, she was advocating the talents of the emerging artists Jenny Holzer, Barbara Kruger, Cindy Sherman and Rosemarie Trockel. Sprüth countered an art market dominated by male artists with a gallery focused on female artists. Her efforts brought these female artists to international prominence. By doing so she also helped previously underappreciated female artists with an entirely new style to establish a reputation. Monika Sprüth made very uncertain, but highly innovative long-term investments in some artists with new styles. Her gallery (now *Sprüth & Magers*) subsequently became highly successful.

The main objective of our paper is to analyze quantitatively whether superstar effects exist in this particular market and if so, to find an adequate approximation of the underlying mechanism for the evolution of art galleries. The paper contributes in three ways to the growing literature on superstar effects. First, we take up ideas from statistical physics to model processes that allow us to analyze the development of different types of distributions of success in the market for art galleries. Second, we apply new methods of empirical testing to determine which distribution best fits our data. Our data reveals lognormal distribution (as the consequence of a geometric Brownian motion) constituting the underlying stochastic process. Third, we offer an economic meaning for this process. In doing so, we hypothesize that the art marketing process is not inherently rudderless, and we propose a reversed version of Baumol's (1986) assumption and suggest that the imperfection of the available information on prices and transactions *does* matter (in the sense that better information about the behavior of the market could help to make decisions more effectively).

The rest of our paper is organized as follows: First we describe the deep-pocket market of art galleries. Then we outline a theoretical model with different versions for the development process of this market. By combining characteristics of the market for art galleries with well-known stochastic processes, the paper offers several theoretical probability density functions which would result from the underlying processes. Thereafter, we empirically test which distribution best fits the data. The last section concludes.

3. Methodological Approach

In this paper, we combine economic analysis with methods from 'econophysics' (see, for instance, the textbook of Sinha et al. 2011). Because such a procedure is rather uncommon, some explanatory remarks seem necessary. Our main research question – as stated above – is a dynamic one: What kind of dynamic economic process takes effect such that a small, inconsequential firm (here an art gallery) becomes dominant in a field? From a purely economic point of view, three main effects are to be expected: 'information' provided by the respective gallery for actual as well as potential art buyers, 'specific investments' in the artists a particular gallery represents and 'competition' from other galleries which are also active in the particular (two-sided) market. Specific investments are tools to gain comparative advantage in the market whereas competition among firms tends to destroy all comparative advantages a particular firm may gain. In short, a Schumpeter (1934, 1942) process of 'creative destruction' is to be expected economically. In economics, the method to check the Schumpeter hypothesis is to construct an economic model and to solve it by comparative static or comparative dynamic methods. An econometric analysis with an estimation equation based on the results of the comparative static or comparative static results would then follow suit.[18]

However, the disadvantage of this conventional approach is that it says almost nothing about the dynamic process that governs the empirical results, i.e., the process is a 'black box'. As is well-known, economic processes over time are not deterministic and, hence, one cannot be sure that the results of the process are due to economic variables or pure chance. Instead of applying standard economic analysis only, we employ methods form statistical physics (also called 'econophysics') to construct a model of investment and competition for two-sided markets, based on the case of galleries. In contrast to economics, in econophysics dynamic processes can be specified by a number of rather well-known stochastic processes. Most interestingly, these stochastic processes lead to different distributions of the variable under investigation (here the success of art galleries). The empirical distribution of the success variable can be tested as to which theo-

[18] A Schumpeterian perspective is also taken by Etro and Pagani (2012) who analyze the determinants of the prices of paintings.

retical distribution fits best the empirical one. If the result is coherent, it is possible to draw a conclusion on the dynamic process that generated the distribution. In such a way the stochastic process can be identified. Having identified the dynamic process, the economic mechanism of interaction between galleries' investments and competition can be determined.

The method applied in this paper is as follows: First, the ranking of galleries with respect to their success of promoting artists is formalized. Second, several specified dynamic approaches from statistical physics are employed to model the development of success of art galleries over time. These specified dynamic processes possess well-defined distributions for the success variable of the paper. Third, it is tested which of these distributions fits best the empirical distribution of the success variable.

4. The Market for Art Galleries

Worldwide there are about 18,000 art galleries, 22,000 museums or art collections, 1,500 auction houses and 500 fairs, quite recently spanning a market of a double-digit billion dollar volume (Artprize 2011).[19] We use the German art market as a *pars pro toto* for the global art industry. According to BMWi (2009a) and BMWi (2009b), with an annual turnover of nearly €2 billion in 2008, this art market is one of the smallest branches of the creative industry.[20] This volume is more or less equally distributed among artists (39%), exhibitions (31%) and the art trade (e.g. auctioneers, galleries; 30%). The dominant galleries and art dealers generate a significant percentage of their turnover abroad. Most of the approximately 1,900 German galleries are single person firms or at least very small enterprises. At most 40 to 50 galleries compete successfully in the international art market.

Artists who intend to sell their works attempt to do so by using art galleries as middlemen. Galleries are the intermediaries between artists and both art investors and art collectors. The ever-growing demand for the information services of intermediaries should have a positive impact on the likelihood of success for 'qualified' art dealers. But do the economics of the gallery sector support the long-term success of individual actors?

Concerning market entry, no specific qualification such as a degree in arts, art history or in economics, is necessary to open a gallery. Other relevant barriers to entering the art market appear to be predominantly absent. Neither economies of scale nor extraordinary capital requirements can be detected from the outset. Switching costs appear to be relatively low and in terms of the concept of Porter's 'five forces', only moderate threats – apart from the threat of entry – affect the market. Galleries choose and promote particular artists who represent the 'supplier side' in this model framework. The corresponding bargaining power of the individual artist only rises with growing reputation and success in the art market, but initially it is very low.

[19] In the course of the worldwide economic crisis of 2008, the art market collapsed, but it has been gradually recovering since 2009.

[20] This means 1.5% of the creative industry and 0.04% of the overall economy. Aside from any economic figures, the importance of the art market in terms of reputation building (e.g. for cities) should be emphasized.

In contrast, the bargaining power of the 'buyer side' (e.g. private collectors) has recently tended to grow (Artprize 2011). However, successful galleries serve a specific wealthy clientele whose purchases of works of art are supposedly price inelastic.

In addition, 'rivalry' among galleries is not such an issue as it obviously is in other economic sectors. Keeping in close contact with other galleries as well as with collectors, artists and museums is essential for successfully communicating the galleries' visions and realizing their strategic ambitions. Because credence, inspection and experience are central characteristics of art-dealing, art galleries play a key role in determining the development of a whole industry.

Although barriers to entry do not exist to any great extent, the most surprising empirical fact is perhaps the control of this large sector by only a hundred persons. This emphasizes the relevance of a reputation building process in the market for artworks.

Investing in the most recent contemporary art is a very risky endeavor. At the point of a first investment in an artist, it is almost impossible to predict the likelihood of success. One of the reasons, is that this kind of art needs to be subjected to the test of time, i.e., people will have to determine whether an artwork has intrinsic aesthetic value or not.[21] So it could well be, that the value creation of an artwork is a process in which the work creates its own success, based on an information cascade (Bikhchandani et al. 1992; Chamley 2004, pp.58; Watts 2002) triggered somewhere in the world of arts. A gallery that was successful in the past may have the advantage of having gained an expert reputation in the selection of future trends compared to less successful galleries. The success of such a gallery suggests expertise in predicting future trends, which will lead to creating those trends. Taking the selection of a successful gallery as a signal for a future trend, investors and collectors will invest in the works and artists represented by that gallery which, as a consequence, will become even more successful. In this way a successful gallery could create self-fulfilling prophecies about future trends through its own selections.

---

[21] In a sense, this kind of value creation resembles the pricing processes in the stock market or the selection of a new restaurant whose quality is unknown up to that point (Banerjee 1992; Becker 1991; Karni and Levin 1994).

The economic question therefore remains: How can a gallery that was successful in the past gain an ever increasing reputational advantage as an expert in the selection of future trends compared to less successful galleries?

5. Model

As the most crucial empirical aspect of the arts market, the dominance of a few galleries (ranked by their success in promoting previously unknown artists) in the market is taken for granted. Since art galleries are in the middle between unknown artists and ignorant potential art buyers, this is a version of a two-sided market. (For a definition and the conceptual background of the latter see, e.g., Rochet and Tirole 2003, 2004, 2006; Rysman 2009.) Rather than analyzing pricing of gallery services and art works, the objective is here to model 'success' of art galleries in the above sense. As in most markets – whether one-sided or two-sided – competition, innovation and information are among the usually expected success factors. However, it is not at all clear how the dynamics of success are to be determined in a market that is prone to high-level quality uncertainty. Instead of employing a purely (more or less static) economic model, it seems more adequate here to use economic ideas of competition, innovation and information and combine them with known dynamic processes of statistical physics.[22] In such a way it seems possible to integrate economic knowledge of markets and their underlying evolutionary dynamics.

To analyze the success of galleries in a two-sided market, its success has to be defined quantitatively. Let X_i be the number of points a gallery i ($i = 1, \ldots, N$) gains by representing artists who have recently become highly esteemed. For instance, take the top-ten ranking of artists and allocate a certain number of points to each of the places in the ranking, with the largest number of points to be allocated to the highest-ranked artist and so on in descending order:

$$X_1 > X_2 > \ \ldots \ > X_N. \qquad (1)$$

Obviously, i is the rank of gallery X_i. According to Stanley et al. (1995) the ranking can be formalized as follows:

$$\frac{i}{N} = 1 - F(X_i) \qquad (2)$$

[22] For a representative sample of research in this field see the papers in the Journal of Dynamics and Control 32(1), 2008: 1-320: "Applications of statistical physics in economics and finance".

or equivalently:

$$\ln i = \ln[1 - F(X_i)] + \ln N, \quad (3)$$

with $F(X_i)$ as the cumulative distribution function of X_i.

The question is what kind of distribution the observations X_i of the gallery success performance measure will follow.

First of all, there is competition among galleries for success with the artists they represent. It is well known that competition has an equalizing effect on the relative success of competitors. This actually is one of the main effects of competition. Therefore, the relative success of galleries will have a tendency to the mean success, μ:

$$dX_i(t) \propto \theta \cdot \left(\mu - \lambda \cdot X_i(t)\right) \quad (4)$$

with:

$dX_i(t)$: the change of $X_i(t)$ over time t,

μ: mean value of success $X_i(t)$ with $\mu > 0$,

θ: parameter for the speed of reversion to the mean, $\theta > 0$, and

λ: parameter with which the state of $X_i(t)$ enters the mean-reverting process, $0 \leq \lambda \leq 1$.

In (4), θ is a parameter that measures the speed with which deviations from the mean return to it again. This speed of convergence may be interpreted as the degree of competition intensity on the respective market. Put differently, $1/\theta$ could be defined as a measure of market failure. With this interpretation, μ would be the long-term equilibrium success value for galleries in a competitive market.

The parameter λ measures the influence of the state variable X_i in the mean-reverting process. Since it is assumed to be in the range between zero and unity, even large states of X_i may have a small influence on the mean-reverting process. Economically this may mean that highly successful galleries support the mean-reverting effect of the competition between galleries to only a minor extent. A reason for this may be that the galleries undertook long-term investments in some artists (with new styles) that later became highly successful and that this investment is unique, or at least well-nigh impossible to imitate. A good example of both a very successful and a very innovative gallery is the above mentioned gallery, *Sprüth & Magers*. Advocating female artists with a new style, Monika Sprüth gave birth to several star artists of international reputation.

In a sense, λ may be interpreted as a measure of the degree of innovation in arts[23] which was triggered by high-risk investments in some artists. The innovation is the greater the smaller λ is.

A first model for the success of galleries (or even success in two-sided markets with high quality uncertainty), particularly for the achievements of galleries, can be formalized as follows. Let the dynamics of X_i be described by the following stochastic differential equation:

$$dX_i(t) = \theta \cdot \big(\mu - X_i(t)\big)\, dt + \sigma \cdot X_i(t)\, dW(t) \tag{5}$$

with:

σ: variance of $X_i(t)$, $\sigma > 0$, and

$dW(t)$: a standard Wiener process with zero mean and standard deviation $(dt)^{1/2}$.

In (5) – the dynamic process constitutes an *inhomogeneous geometric Brownian motion* (Bhattarchaya 1978; Zhao 2009) – the innovation effect λ is set to unity.[24] In this case, there is a mean-reversion effect of competition which depends on the parameter θ; in (5) this effect is independent of the innovation effect that is assumed to be a normally distributed random variable. Moreover, as already indicated above, θ depicts the speed with which the variable *Xi* converges to its mean, μ. A high θ signals economically a very quick convergence, and *vice versa*.

[23] Here innovation only means that, e.g., some new style is chosen which is substantially *different* from the prevailing style.

[24] This dynamic process for X_i is an adaptation of the model of Wyart and Bouchaud (2003, p. 248) – which is analyzed more rigorously in Bouchaud and Mézard (2000). See also Bouchaud (2001, pp. 107, 110) for the dynamics of the distribution of wealth. However, the economic interpretation of the process is quite different from their interpretation. See Appendix D for a further explication of the derivation of (5) from Wyart and Bouchaud (2003).

For art galleries (and presumably various other intermediary platforms in two-sided markets), it is to suspect that θ may not be very high. The reason is that there are specific investments required and there are economies of scale and scope: An established gallery may use its expertise and connections to find and promote new artists easier and at lower costs than potential competitors. Hence, even if there is competition between galleries, the speed of mean-reversion of their success might be rather slow.

As shown by Wyart and Bouchaud (2003), referring to Bouchaud and Mézard (2000), the stationary distribution for this process is $p(x) \sim x^{-1-(1+\theta/\sigma_0^2)}$ (with $p(x)$ as the probability density of X_i) which has a power-law tail. Hence, if (5) was the correct model for art galleries, one should find a *power-law distribution* as the best fit for the distribution of X_i.[25]

However, besides the competition effect measured by θ and the innovation effect measured by λ, there might be an additional effect associated with art galleries. This group of effects is formed by the information cascades mentioned above. Suppose that art investors consider X_i as a signal for the success of gallery i in predicting the value of an artist it represents. To have an influence on the investors' behavior, X_i must contain information that overrules the personal information investors may already have (Chamley 2004). Because the intrinsic value of artworks is a matter of aesthetic taste, and because aesthetic taste is at the market level, a collective rather than a personal matter, only success of a gallery above the mean success level contains information that is more valuable than the investors' privately-held information (i.e., their personal aesthetic taste). Hence, for being a signal that contains information on the ability of a gallery to predict the collective aesthetic value of artworks, $X_i > \mu$ is required. Therefore it might be the case that:

$$dX_i(t) \propto \frac{X_i(t)}{\mu}. \qquad (6)$$

Relation (6) implies that 'success breeds success'. This may be interpreted as the consequence of a very high ambiguity with respect to the aesthetic value of most contemporaneous artworks.

[25] See also *Power-Law Distribution* in Appendix B.

In a sense, processes of the 'success breeds success' kind create the value of the works they represent. In the theory of networks, this effect is attributed to 'preferential attachment': because some nodes in a network are better linked than others, they attract even more new links.[26] In this paper, the final reason for success is the – perhaps accidental – information cascade triggered by the initial success which is taken as a signal of expertise in forecasting profitable art developments.

Combining the competition, innovation and information effects in (4) and (6) as well as taking into account accidental further effects, the process that describes the evolution of the success variable X_i over time may be given by the following stochastic differential equation:

$$dX_i(t) = \theta \cdot \left(\mu - \lambda \cdot X_i(t)\right) \cdot \left(\frac{X_i(t)}{\mu}\right) dt + \sigma \cdot X_i(t) dW(t) \qquad (7)$$

which can be written as:

$$dX_i(t) = \theta \cdot \left(1 - \left(\frac{\lambda}{\mu}\right) \cdot X_i(t)\right) \cdot X_i(t) dt + \sigma \cdot X_i(t) dW(t) \qquad (8)$$

with:

σ: variance of $X_i(t)$, $\sigma > 0$, and

$dW(t)$: a standard Wiener process with zero mean and standard deviation $(dt)^{1/2}$.

The evolution equation in (6) can be interpreted as follows:

(a) For $\lambda = 0$ a *geometric Brownian motion* with $\mu = \theta$ results (e.g. Dixit and Pindyck 1994, p. 71; Metcalf and Hassett 1995):

$$dX_i(t) = \theta \cdot X_i(t) dt + \sigma \cdot X_i(t) dW(t). \qquad (9)$$

In this stochastic process, there is no force that drives the success of galleries back to the long-term mean. In economic terms, this means that there is no effective

[26] This aspect of networks is a big topic in the physics literature on the statistical mechanics of network development; see, for instance, Krapivsky and Redner (2001); Berger et al. (2004).

competition effect. Put differently, there might even be strong competition, e.g. measured by sizeable market entry and exit, but the level of innovation of some leading galleries may be of such importance that their success advantage cannot be competed away.

(b) For $0 < \lambda \leq 1$ a *mean-reverting geometric Ornstein-Uhlenbeck process* emerges from (6) (Dixit and Pindyck 1994, p.161; Metcalf and Hassett 1995). In this version of the model, competition might be effective to a certain extent. As a consequence, all three kinds of effects are effective: information, competition and innovation.

(c) The expected percentage change of the success variable X_i is for $\lambda = 0$ given by θ and for $0 < \lambda \leq 1$ by $\theta \cdot \left(1 - \left(\frac{\lambda}{\mu}\right) \cdot X_i(t)\right)$. Moreover, the expected absolute change is defined by $\theta \cdot X_i(t)$ for $\lambda = 0$ and by $\theta \cdot \left(1 - \left(\frac{\lambda}{\mu}\right) \cdot X_i(t)\right) \cdot X_i(t) = \theta \cdot X_i(t) - \left(\frac{\theta\lambda}{\mu}\right) \cdot \left(X_i(t)\right)^2$ (10)

for $0 < \lambda \leq 1$.[27]

First, the stochastic process without the competition effect, the *geometric Brownian motion* ($\lambda = 0$) in (7) is examined.[28] The probability density of the geometric Brownian motion at a fixed time is formulated by Reed and Jorgensen (2004):

$$f\left(X_i(t)\right) = \left(\frac{1}{\left(X_i(t)\sigma\sqrt{2\pi \cdot t}\right)}\right) \cdot exp\left[\left(\frac{-\left(\frac{\ln X(t)}{X_O} - \left(\theta - \frac{1}{2\sigma^2}\right) \cdot t\right)^2}{2\sigma^2 t}\right)\right] \qquad (11)$$

Hence, the probability density function originates a lognormal distribution with a mean θ.[29] This result is important for the empirical investigation below: If the success of galleries is best de-

[27] See also for this interpretation Epstein et al. (1998, p. 158).

[28] For a solution of the stochastic differential equation (7), see also Appendix C.

[29] See also the definition of the *lognormal distribution* in Appendix B.

scribed by a lognormal distribution, the underlying stochastic process may be a geometric Brownian motion. In the interpretation of the stochastic process adopted here, it implies that galleries are extremely innovative ($\lambda = 0$); competition among galleries under these circumstances only has the effect of driving up or down the average success of galleries to θ instead of μ (θ may or may not be larger than μ). With respect to intermediary platforms in general, the value which is to be expected in this case for θ is not clear. If competition among platform intermediaries induces a business creation effect (i.e., increasing the number or value of completed deals between buyers and sellers) which is larger than the business stealing effect (i.e., reducing the number or value of deals completed by the single platforms), the success variable will increase over the former mean value, and *vice versa*. Hence, it is the interaction of these two effects which is decisive.

Second, the result of the stochastic process with a competition effect ($0 < \lambda \leq 1$), the *mean-reverting geometric Ornstein-Uhlenbeck process* in (6), is analyzed.[30]

(a) A non-trivial solution exists if and only if $2\theta > \sigma^2$ and it is a Gamma density:[31]

$$f(X_i) = \frac{\left[\left[\frac{2\left(\frac{\theta\lambda}{\mu}\right)}{\sigma^2}\right]^{((2(\mu+\lambda))/\sigma^2)-1}\right]}{\Gamma\left(\left(\frac{2\theta}{\sigma^2}\right)-1\right)X_i^{(2\theta/\sigma^2)-2}} \cdot exp\left[\left(\frac{-2\left(\frac{\theta\lambda}{\mu}\right)}{\sigma^2}\right) \cdot X_i\right] \tag{12}$$

(b) For $\sigma \to 0$ a Dirac Delta distribution results whose mass is concentrated in μ/λ.

(c) For $\theta > \sigma^2$, the Gamma density function has a maximum at $X_i = \frac{\mu(\theta-\sigma^2)}{(\theta\lambda)}$ and for $\sigma^2 \epsilon (\theta, 2\theta)$the maximum is 0.

As a consequence, for $2\theta > \sigma^2$ a *Gamma distribution* of the success measure of galleries is to be expected empirically. Based on the economic reasoning in this paper, this result would be in accordance with a geometric Ornstein-Uhlenbeck model for gallery success which implies that

[30] For a solution of the stochastic differential equation (6), see also Appendix C.

[31] See also the definition of the *Gamma distribution* in Appendix B.

galleries could be considerably more innovative. Moreover, the more the parameter λ approaches unity, the lower the level of innovation would be.

In the following empirical analysis we will test which distribution function for $F(X_i)$ in equation (3) above will fit best.

6. Empirical Analysis

In an annual procedure undertaken since 1970, the world's most in-demand artists have been issued (and honored) in ranking lists under the title of *Kunstkompass*. This success and reputation barometer excludes any monetary measure,[32] but considers the number of (single and group) exhibitions in internationally prestigious museums and reviews in famous art magazines. Analyzing the top 100 entities of the *Kunstkompass*-rankings for the years 2001, 2004 and 2008, we corroborate Crane's discovery from 1989, that only a few galleries represent almost all of the most visible and most successful artists.[33] We cover an investigation period of seven years. This restriction is not expected to affect considerably the results in comparison to examining other years. It may also be added that the conjoined study of gallery success and its change over time is not intended in this paper but is an issue for ongoing research. As indicated above, we consider three particular years (2001, 2004 and 2008), assess the galleries' ranking according to the success of artists they promote and analyze empirically the distribution of the galleries' rankings.

To start with, in Figure 14 the accumulated scoring points per gallery, which we interpret as a measure of the galleries' success/reputation, are plotted against their rank.[34]

---

[32] To check the relation between a gallery's reputation according to the *Kunstkompass* score value (X) of the year 2004 and the average price per piece of art promoted by the respective gallery, a correlation test was performed. To do this, the (gallery wise) sum (Y) of the average price per artwork for every single artist promoted was calculated with the assumption that all artists are approximately equally productive. The outcome of the correlation test of X and Y shows a strong relation, but not a perfect one (Kendall's Tau 0,441; Spearman's Rho 0,633 – both at 0.01 level). Although there is a number of ways to model gallery success, we suppose that it seems reasonable to focus on an evaluation based on this type of measurement.

[33] The *Kunstkompass*-ranking was deliberately chosen as a metric for gallery success. Despite the fact that it contains 100 galleries only, a more complete list of galleries would distend the tail of the distribution without changing significantly the results or interpretations of our analysis.

[34] For each gallery we added up the achieved score points of every promoted artist among the top 100 ranks.

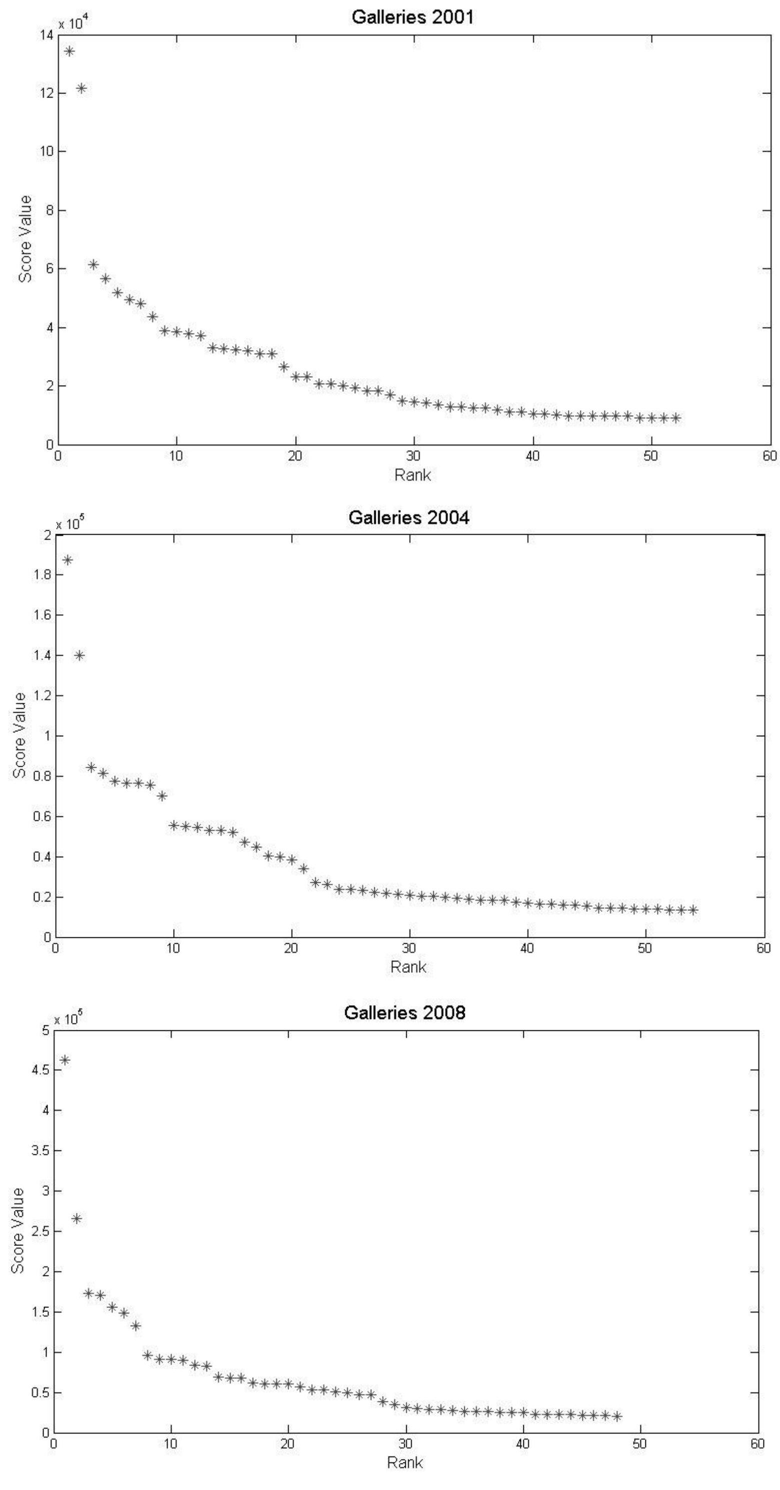


Figure 14. *Rank-Score Plots of the Success of Galleries*

This depiction suggests a distribution which seems to be similar to a power law. Referring to the geometric Brownian motion in (9), another probability distribution intrinsically related to the power law, is the lognormal distribution; e.g., only a small deviation in a multiplicative process[35] decides whether it yields a power law or a lognormal distribution (Champernowne 1953; Gibrat 1930, 1931; Kesten 1973; Simon 1955; Steindl 1965). Displaying the gallery data in log-log plots (see Figure 15), we observe that each year forms what is nearly a straight line, which is a necessary, but not sufficient, condition for the existence of a power-law distribution. In particular Mitzenmacher (2004) emphasizes that this property is also valid for lognormally distributed data, at least approximately, if the variance is large enough.

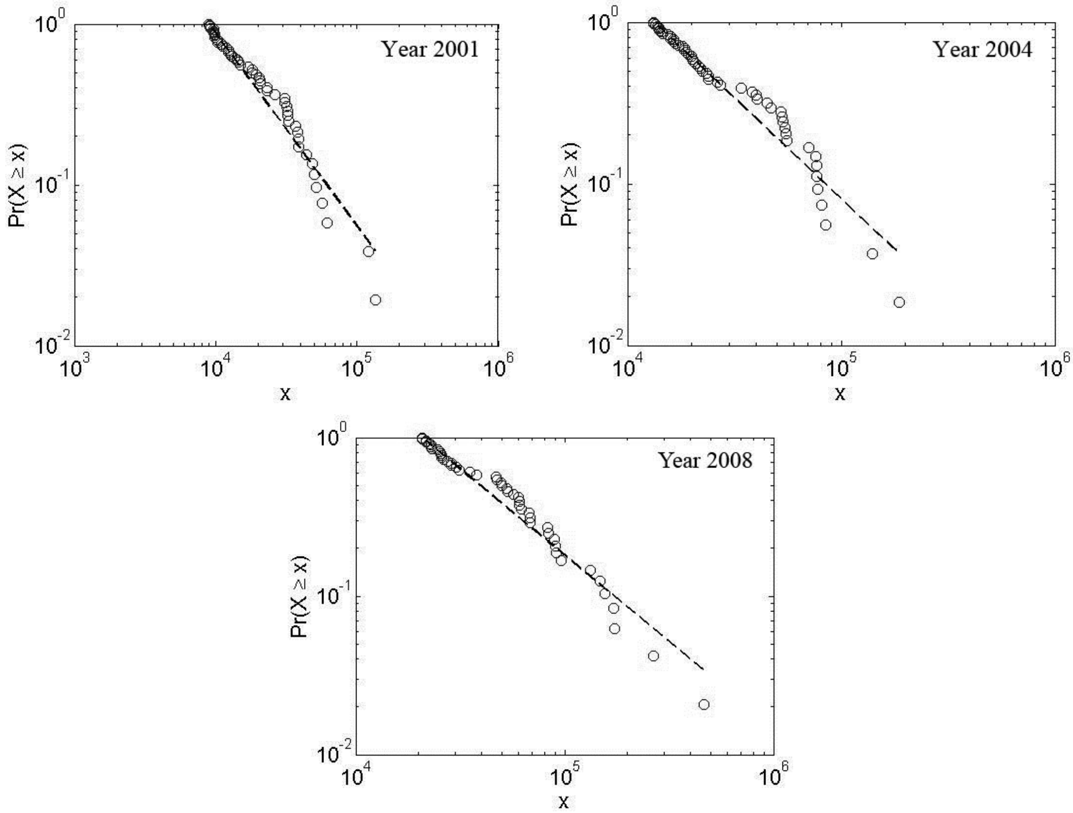


Figure 15. *Log-Log Plots of the Success of Galleries*

---

[35] Multiplicative processes are commonly used to describe the growth of organisms or networks.

The previous considerations concerning the *inhomogeneous geometric Brownian motion*, the *geometric Brownian motion* and the *geometric Ornstein-Uhlenbeck process*, lead us to the following hypothesis:

Success of art galleries follows a power law, a lognormal distribution or a Gamma distribution.

To exclude other similar, potentially competing distributions, a one-sample Kolmogorov-Smirnov test (KS-test) is applied; the result is that the assumption of an exponential, a Poisson, as well as of a normal distribution is not statistically significant for each of the years 2001, 2004 and 2008 (at a significance level of .05). Then a KS-test is applied again to the data in order to test for a lognormal distribution. For the years 2008 and 2001 our hypothesis of logarithmic normality turns out to be statistically significant, but not for 2004. Eliminating the four galleries with the lowest accumulated score values from the 2004 data, a significant test result for this year (significance level .05) is found, too. The fitted parameters are shown in Table 27. Figure 16 displays a probability plot comparing this distribution (dashed line) with the actual distribution in the gallery data.

Year	**2001**	**2004**	**2008**
μ	9.9179	10.2788	10.8408
σ	0.6952	0.6842	0.7494

Scaling parameters of the lognormal distribution
μ: mean
σ: standard deviation

Table 27. *Fitted Parameters According to the Lognormal Distribution*

Year	**2001**	**2004**	**2008**
α	2.1965	2.2465	2.0869

α: scaling parameter of the power-law distribution

Table 28. *Fitted Parameters According to the Power-Law Distribution*

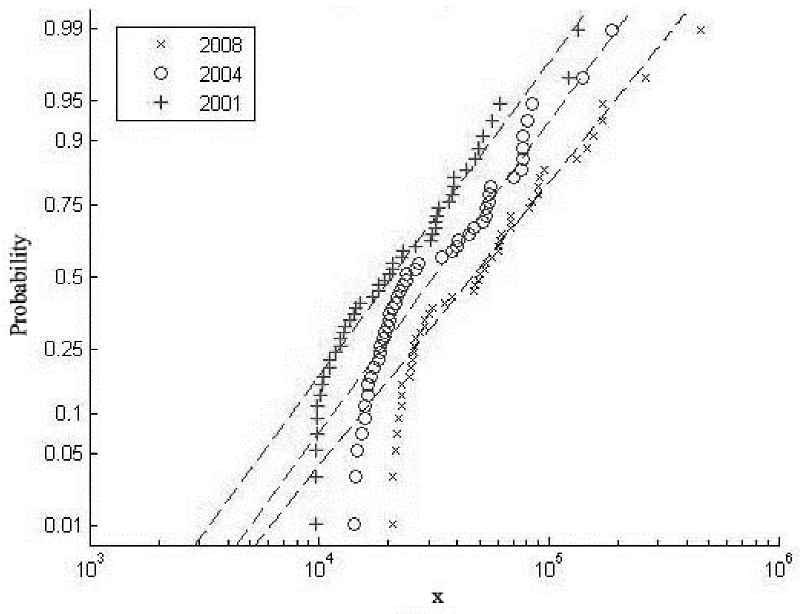


Figure 16. *Probability Plot for Lognormal Distribution of the Success of Galleries*[36]

To test the power-law hypothesis more rigorously, we employ the recent algorithm developed by Clauset et al. (2009) for analyzing power-law distributed data: First we fit the datasets to power-law configurations. Particularly we obtain the following maximum likelihood estimates of the scaling exponent α shown in Table 28.[37] After this the KS-statistics for each of the datasets from 2001, 2004 and 2008 are computed.

For the further analysis, again following Clauset et al. (2009), 1000 synthetic power-law datasets (with n = 300 observations each) are constructed for each of the three datasets from 2001, 2004 and 2008, respectively selecting the scaling parameter α (see Table 28) and the minimum threshold value equal to those of the distribution that best fits the observed data. After running the same fitting-procedure from above for the synthetic power-law datasets, we compute their corresponding KS-statistics. Eventually, the p-value is defined as the ratio of the synthetic KS-statistics which exceed the KS-statistic of the empirical data. We get a clear result for all three

---

[36] The ordinate axis' scale depicts the success probability based on a lognormal distribution; the axis of abscissae has a log scale.

[37] See also *Power-Law Distribution* in Appendix B.

datasets indicating that the power-law hypothesis has to be ruled out. It is worth noting that this result is obtained with the relatively lenient rule $p \leq 0.05$.

Finally, the data are fitted with the maximum-likelihood method according to the assumption of a Gamma distribution; the parameters are presented in Table 29. A chi-square goodness-of-fit test at the .05-significance level is carried out with the result that the assumption of a Gamma distribution can be ruled out for each of the datasets of 2001, 2004 and 2008.

Year	**2001**	**2004**	**2008**
$\boldsymbol{\alpha}$	1.9785	2.0566	1.6760
$\boldsymbol{\beta}$	1.3482e+004	1.8400e+004	4.2255e+004

α, β: Scaling parameters of the Gamma distribution

Table 29. *Fitted Parameters According to the Gamma Distribution*

Put briefly, our observations are consistent with the hypothesis that the data are drawn from a lognormal distribution. In Figure 17, the estimated (lognormal) complementary cumulative distribution functions (CCDFs) for the years 2001, 2004 and 2008 are contrasted with the respective empirical CCDF.

Concerning distributions connatural to power laws, the CCDF is linearly related to size:

$$\log P(x > x_o) \approx c - \alpha \log(x_0), \qquad (13)$$

where c is a constant and α the scaling parameter.[38]

This means, (12) becomes an exact approximation as $x_o \to \infty$ and therefore indicates Figure 17 to be a convenient depiction to assess the fit of data to power-law related distributions (Dinardo and Winfree 2010). We choose this display to highlight the fit of our data to the lognormal distribution for all three years examined (globally and particularly in its tail).

[38] See above, and also *Power-Law Distribution* in Appendix B.

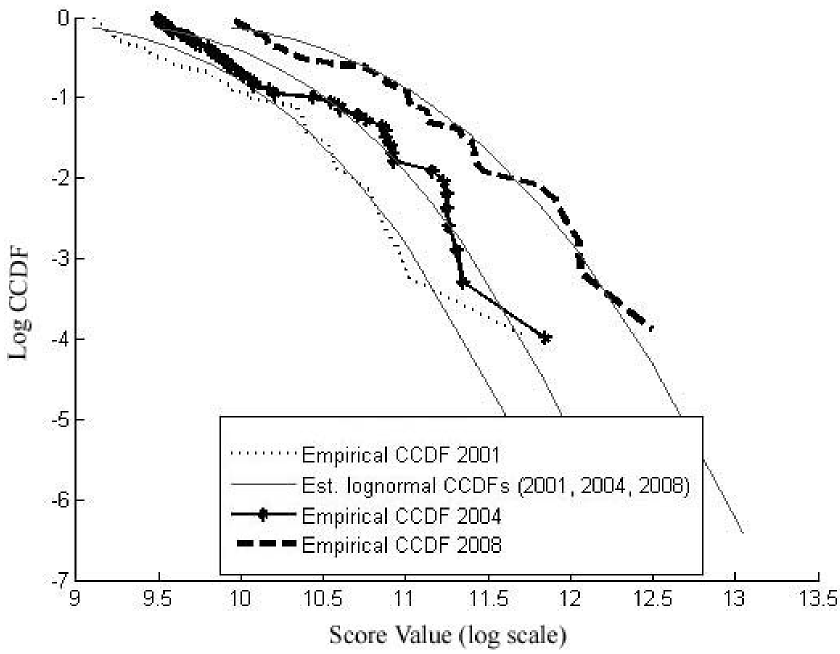


Figure 17. *Log-Log Plot of Complementary Cumulative Distribution Functions of the Success of Galleries*

7. Conclusions

In this paper, the evolutionary dynamics of economic processes that are driven by competition, innovation and information are formalized by combining economic knowledge with dynamical methods of physics. The information aspect is of special interest here since the dynamic success of galleries (and other platform intermediaries) is investigated whose main task is to reduce quality uncertainty and to promote deals between suppliers and demanders. The emphasis of the paper is put on identifying and separating competition, innovation and information effects. Furthermore, it is shown how the most likely dynamic process (among the potential processes) can be identified empirically. Galleries as platform intermediaries in the two-sided market of contemporary art are a good example in this respect.

Galleries are central to the promulgation of new works of art to investors and collectors, because they operate at the customer's interface of the cultural value chain. In a certain sense, the artistic decisions and financial investments of gallery owners promote the reputation of both works and artists. Hence, galleries deem to be good examples for intermediary platforms in two-sided markets. The method applied as well as the results gained may be extendable to other intermediary platforms in two-sided markets with a high level of quality uncertainty and innovation.

The success of galleries is expected to depend crucially on three determinants: an information effect, an innovation effect and a competition effect. Employing the above mentioned methods, it is demonstrated theoretically that these determinants may support different empirical characteristics of the measurable success of art galleries.

Empirically, we find the success of galleries to be best described by a lognormal distribution which means that the underlying stochastic process is most likely a geometric Brownian motion. In the interpretation of this stochastic process given here, this implies that galleries are very innovative. Moreover, it seems that the (loosely defined) degree of innovation of a few leading galleries is supported over time by information cascades in such a way that their success advantage cannot be eroded by competition. This means that there is no force which drives the success of galleries back to the long-term mean. Even if there was strong competition, e.g. measured by sizeable market entry and exit, the degree of innovation of some leading galleries may have been of great importance. In fact, very successful galleries start building up a reputation by being very innovative in the first place.[39] As the case of the acclaimed gallery owner Monika Sprüth has illustrated, she has helped to establish a reputation for previously underappreciated female artists with a new style. Her efforts brought those female artists to international prominence and success for her new gallery too.

This initial innovation can become a starting-point for information cascades: reputable galleries are followed by experts, collectors and museums (Crossland and Smith 2002). Prominent galleries can even have an impact on artists, persuading them to reshape their creative style towards works which may have higher commercial potential (Currid 2007). In a certain sense, experts in other fields that are prone to high levels of quality uncertainty may be considered as intermediary platforms, even if there is no institutionalized connection between the intermediary and the suppliers and demanders on these markets. Having established a high reputation for quality sensitivity, experts for technical systems as well as restaurant or travel guides may gain a market position that is not contestable. In a similar way, financial intermediaries as, e.g., banks with specific knowledge about firms and their investment projects may also gain uncontestable positions with respect to firms and investors. More generally, two-sided markets with high quality uncertainty or information deficits on the one hand and high levels of specific investments of the respective intermediary on the other hand seem to function in a similar way as art galleries with respect to artists and collectors or investors.

Investments in works of art cannot be separated from their social context, i.e., the exclusive art world in a wider sense. By choosing the most notable and respected art galleries, customers minimize the search costs of gaining endorsement by discussion partners in that world (Adler 1985). Robinson’s (1961, p. 398) remark that “…fashion serves as a means of demonstrating

[39] We cannot exclude the problem that by examining the survivors, we are really only looking at those gallery ‘strategies’ that were ex post successful (see Brown et al. 1992). However, we do not consider this a considerable effect because of the absent barriers to entry that characterize the industry.

command over current, as opposed to former, output", seems to be directly applicable to the arts, too. As art investors and collectors cannot be equally well informed about each and every gallery, they will choose a limited number of preferred galleries whose exhibited works are innovative according to the public discourse, which means that they are 'demonstrating command over current' (Robinson 1961, p. 398). Following Adler (1985), Star galleries absorb part of consumers' savings in search costs – including the 'entrance fees' to exclusive art circles – by demanding high prices and receiving public reputation for their products. Thus, the superstar effect in the case of galleries can be understood as an appropriation of *search and entrance costs* which emerge whenever consumption requires special knowledge and social inclusion.

In a continuous process, a few star galleries develop and seem to be able to establish an uncontestable market position. This result is in line with the findings of Salganik et al. (2006) and Salganik and Watts (2008) that social influence contributes very strongly to the inequality of outcomes in cultural markets. Contrary to the finding by de Vany and Walls (1999) that past success does not predict future success in the movie industry,[40] forecasts of expected gallery success are not completely meaningless: the underlying stochastic processes of success may help to improve our understanding of the evolution of superstar effects in the art markets. It is neither supposed nor claimed that the identified/hypothesized process is fixed and that it will never change, but it seems to provide a useful (first) approximation.

In addition to these results, we find that also economic peculiarities may be main drivers of the evolution of success (not only) in cultural markets when quality uncertainty is high for the final customers and when on the side of the intermediary platform specific investments are required to build up a sustainable reputation with both artists as well as art collectors and investors. Having established such a reputation, competition among intermediary platforms plays hardly any role. It seems very likely that this result could be generalized for other two-sided markets with high quality uncertainty.

[40] De Vany and Walls (1999) argue that when the audience makes a movie a hit, no amount of "star power" or marketing can alter that, because movies' box-office possibilities are Lévy-distributed, i.e. their means and variances are not finite.

With a growing number of two-sided markets with platform intermediaries, the methods applied in this context may be suitable to differentiate between competition, innovation and information effects in these markets. The detailed adoption of the approach considered here to other industry-specific platforms and the examination of differences concerning transferability, limitations and empirical evidence is a topic of further research.

8. References

Adler, Moshe (1985). Stardom and talent. *The American Economic Review*, 75(1), 208–212.

Artprize (2011). *Art market trends 2011*. Saint-Romain-au-Mont-d'Or: Artprize.

Banerjee, Abhijit V. (1992). A simple model of herd behavior. *Quarterly Journal of Economics*, 107(3), 797–817.

Baumol, William J. (1986). Unnatural value: Or art investment as a floating crap game. *The American Economic Review*, 76(2), 10–14.

Bhattarchaya, Sudipto (1978). Project valuation with mean-reverting cash flow streams. *Journal of Finance*, 33(5), 1317–1331.

Becker, Howard S. (1982). *Art worlds*. Berkeley, Los Angeles: University of California Press.

Becker, Gary S. (1991). A note on restaurant pricing and other social influences on prices. *Journal of Political Economy*, 99(5), 1109–1116.

Berger, Noam, Christian Borgs, Jennifer T. Chayes, Raissa M D'Souza, and Robert D. Kleinberg (2004). Competition-induced preferential attachment. *Automata, Languages and Programming, Lecture Notes in Computer Science*, 3142(1), 208–221.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch (1992). A theory of fads, fashion, custom and cultural change as informational cascades. *Journal of Political Economy*, 100(5), 992–1026.

BMWi (2009a). *Initiative Kultur- und Kreativwirtschaft – Branchenhearing Kunstmarkt*. Berlin: Bundesministerium für Wirtschaft und Technologie.

BMWi (2009b). *Kultur- und Kreativwirtschaft: Ermittlung der gemeinsamen charakteristischen Definitionselemente der heterogenen Teilbereiche der „Kulturwirtschaft" zur Bestimmung ihrer Perspektiven aus volkswirtschaftlicher Sicht*. Köln/Bremen/Berlin: Bundesministerium für Wirtschaft und Technologie.

Bouchaud, Jean-Philippe (2001). Power laws in economics and finance: some ideas from physics. *Quantitative Finance*, 1(1), 105–112.

Bouchaud, Jean-Philippe, and Marc Mézard (2000). Wealth condensation in a simple model of economy. *Physica*, 282(3-4), 536–545.

Brown, Stephen J., William Goetzmann, Roger G. Ibbotson, and Stephen A. Ross (1992). Survivorship bias in performance studies. *The Review of Financial Studies*, 5(4), 553–580.

Camarero, Carmen, Maria J. Garrido, and Eva Vicente (2011). How cultural organizations' size and funding influence innovation and performance: the case of museum. *Journal of Cultural Economics*, 35(4), 247–266.

Canals-Cerdá, and José J. (2012). The value of a good reputation online: an application to art auctions. *Journal of Cultural Economics*, 36(1), 67–85.

Caves, Richard (2000). *Creative industries: Contracts between art and commerce*. Cambridge: Harvard University Press.

Champernowne, David G. (1953). A model of income distribution. The *Economic Journal* 63(250), 318–351.

Chamley, Christopher P. (2004). *Rational herds. Economic models of social learning*. Cambridge: Cambridge University Press.

Clauset, Aaron, Mark E.J. Newman, and Cosma R. Shalizi (2009). Power-law distributions in empirical data. *SIAM Review*, 51(4), 661–703.

Crane, Diane (1989). *The transformation of the avant-garde: The New York art world. 1940–1985*. Chicago: The University of Chicago Press.

Crossland, Philip, and Faye I. Smith (2002). Value creation in fine arts: A system dynamics model of inverse demand and information cascades. *Strategic Management Journal*, 23(5), 417–434.

Currid, Elizabeth (2007). *The Warhol Economy: How fashion, art and music drive New York City*. Princeton, New Jersey: Princeton University Press.

De Vany, Arthur, and William D. Walls (1999). Uncertainty in the movie industry: Does star power reduce the terror of the box office?. *Journal of Cultural Economics*, 23(4), 285–318.

Dinardo, John E., and Jason A. Winfree (2010). The law of genius and home runs refuted. *Economic Inquiry*, 48(1), 51–64.

Dixit, Avinash K., and Robert S. Pindyck (1994). *Investment under uncertainty*. Princeton, New Jersey: Princeton University Press.

Ehrmann, Thomas, Brinja Meiseberg, and Christian Ritz (2009). Superstar effects in deluxe gastronomy – An empirical analysis of value creation in German quality restaurants. *Kyklos*, 62(4), 526–541.

Epstein, Debbie, Nick Mayor, Philipp Schönbucher, Elizabeth Whalley, and Paul Wilmott (1998). The valuation of a firm advertising optimally. *The Quarterly Review of Economics and Finance*, 38(2), 149–166.

Etro, Federico, and Laura Pagani (2012) The market for paintings in the Venetian republic from Renaissance to Rococó. *Journal of Cultural Economics*, DOI: 10.1007/s10824-012-9191-5.

Ewald, Christian-Oliver, and Zhaojun Yang (2007). Geometric mean reversion: Formulas for the equilibrium density and analytic moment matching. *Risk Management eJournal*, DOI: 10.2139/ssrn.999561.

Filimon, Nela, Jordi López-Sintas, and Carlos Pádros-Reig (2011). A test of Rosen's and Adler's theories of superstars. *Journal of Cultural Economics*, 35(2), 137–161.

Franck, Egon, and Stephan Nüesch (2007). Avoiding 'star wars' – Celebrity creation as media strategy. *Kyklos*, 60(2), 211–230.

Frey, Bruno S. (1997). Evaluating cultural property: The economic approach. *International Journal of Cultural Property*, 6(2), 231–246.

Frey, Bruno S. (1998). Superstar museums: An economic analysis. *Journal of Cultural Economics*, 22(2–3), 113–125.

Frey, Bruno S., and Stephan Meier (2006). The economics of museums, in: Victor A. Ginsburgh, and David Throsby (eds.), *Handbook for economics of art and culture*. Amsterdam: North-Holland, 1017–1047.

Gibrat, Robert (1930). *Une loi des réparations économiques: l'effet proportionnel*. Bulletin de Statistique Générale, France 19, 469.

Gibrat, Robert (1931). *Les inégalités économiques*. Paris: Recueil Sirey.

Ginsburgh, Victor (2003). Awards, success and aesthetic quality in the arts. *Journal of Economic Perspectives*, 17(2), 99–111.

Hutter, Michael, and David Throsby (2008). *Beyond price. Value in culture, economics, and the art*. Cambridge: Cambridge University Press.

Jetschke, Gottfried (1989). *Mathematik der Selbstorganisation*. Berlin: VEB Deutscher Verlag der Wissenschaften.

Karni, Edi, and Dan Levin (1994). Social attributes and strategic equilibrium: A restaurant pricing game. *Journal of Political Economy*, 102(4), 822–840.

Kesten, Harry (1973). Random difference equations and renewal theory for products of random matrices. *Acta Mathematica*, 131(1), 207–248.

Kloeden, Peter E., and Eckhard Platen (1992). *Numerical solution of stochastic differential equations*. Berlin: Springer.

Krapivsky, Paul L., and Sidney Redner (2001). Organization of growing random networks. *Physical Review E*, 63(6), 066123–1–066123–14.

Metcalf, Gilbert E., and Kevin A. Hassett (1995). Investment under alternative return assumptions. Comparing random walks and mean reversion. *Journal of Economic Dynamics and Control*, 19(8), 1471–1488.

Mitzenmacher, Michael (2004). A brief history of generative models for power law and lognormal distributions. *Internet Mathematics*, 1(2), 226–251.

Nelson, Randy A., and Robert Glotfelty (2012). Movie stars and box office revenues: an empirical analysis. *Journal of Cultural Economics*, 36(2), 141–166.

Pasquali, Sara (2001). The stochastic logistic equation: stationary solutions and their stability. *Rendiconti del Seminario Matematico della Università di Padova*, 106, 165–283.

Pitt, Ivan L. (2010). Superstar effects on royalty income in a performing rights organization. *Journal of Cultural Economics*, 34(3), 219–239.

Reed, William J., and Murray Jorgensen (2004). The double-pareto-lognormal distribution – A new parametric model for size distributions. *Communications in Statistics – Theory and Methods*, 33(8), 1733–1753.

Robinson, Dwight E. (1961). The economics of fashion demand. *Quarterly Journal of Economics*, 75(3), 376–398.

Rochet, Jean-Charles, and Jean Tirole (2003). Platform competition in two-sided markets. *Journal of European Economic Association*, 1(4), 990–1029.

Rochet, Jean-Charles, and Jean Tirole (2004). Defining two-sided markets. IDEI and GREMAQ, Toulouse: Working paper.

Rochet, Jean-Charles, and Jean Tirole (2006). Two-sided markets: a progress report. *The RAND Journal of Economics*, 37(3), 645–667.

Rosen, Sherwin (1981). The economics of superstars. *American Economic Review*, 71(5), 845–858.

Rysman, Marc (2009). The economics of two-sided markets. *Journal of Economic Perspectives*, 23(3), 125–143.

Salganik, Matthew J., Peter S. Dodds, and Duncan J. Watts (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, 311(5762), 854–856.

Salganik, Matthew J., and Duncan J. Watts (2008). Leading the herd astray: An experimental study of self-fulfilling prophecies in an artificial cultural market. *Social Psychology Quarterly*, 71(4), 338–355.

Schönfeld, Susanne, and Andreas Reinstaller (2007). The effects of gallery and artist reputation on prices in the primary market for art: a note. *Journal of Cultural Economics*, 31(2), 143–153.

Schumpeter, Joseph A. (1934). *The theory of economic development*. New York: Oxford University Press.

Schumpeter, Joseph A. (1942). *Capitalism, socialism and democracy*. New York: Harper and Brothers.

Simon, Herbert A. (1955). On a class of skew distribution functions. *Biometrika*, 42(3–4), 425–440.

Sinha, Sitabhra, Arnab Chatterjee, and Anirban Chakraborti (2011). *Econophysics*. An introduction. Weinheim: Wiley-VCH.

Stanley, Michael H.R., Sergey V. Buldyrev, Shlomo Havlin, Rosario N. Mantegna, Michael A. Salinger, and Eugene H. Stanley (1995). Zipf plots and the size distribution of firms. *Economics Letters*, 49(4), 453–457.

Steindl, Josef (1965). *Random processes and the growth of firms*. New York: Hafner.

Walls, William D. (2010). Superstars and heavy tails in recorded entertainment: empirical analysis of the market for DVDs. *Journal of Cultural Economics*, 34(4), 261–279.

Watts, Duncan J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Science*, 99(9), 5766–5771.

Wyart, Matthieu, and Jean-Philippe Bouchaud (2003). Statistical models for company growth. *Physica A*, 326(1-2), 241–255.

Zhao, Bo (2009). Inhomogeneous geometric Brownian motion. *Derivatives eJournal*, DOI: 10.2139/ssrn.1429449.

APPENDIX A

EXPLANATION OF THE PARAMETERS SUBOPTIMAL AND BEYOND OPTIMAL

To assess the optimality of customers' contract choices *ex post*, we set up the following framework of BahnCard choice and usage: Let $(L_i, \alpha p)$ be a contract where L_i stands for different fixed fees that result in different variable fee rebates α on ticket price p. This contract enables customers to use a train for a fee αp, once the flat fee L_i is paid. There are two extreme cases: the flat rate $(L, 0)$, which corresponds to the BC100 and the pay-per-mile tariff $(0, p)$, which is equivalent to not using a BahnCard at all. The BahnCards under consideration in our analysis have either rebates α of 25% or 50% on p. Let v be the total amount spent on rail travel during the validity period of a BahnCard (based on the regular fare), then the lower optimality boundaries of the examined BahnCard contracts are given by

$$L_{25} + 0.75v \geq L_{50} + 0.5v \geq L_{100} \tag{A1}$$

and thus $v_{25}^{l} = L_{25}/0.25,$ (A2)

$$v_{50}^{l} = (L_{50} - L_{25})/0.25 \tag{A3}$$

and $v_{100}^{l} = (L_{100} - L_{50})/0.5.$ (A4)

The binary parameters *suboptimal* and *beyond optimal* are calculated according to this scheme.

APPENDIX B

RELEVANT DISTRIBUTIONS

Power-Law Distribution

A quantity x obeys a power law, if it is drawn from a probability distribution

$$p(x) \propto x^{-\alpha} \tag{B1}$$

where $\alpha > 0$ is a constant scaling parameter.

(In practice, only a few empirical phenomena follow a power-law distribution for all values of x, but often the power law can be applied for values above a certain threshold x_{min}.)

Lognormal Distribution

A random variable X obeys a lognormal distribution, if its logarithm is normally distributed. The probability density function of a lognormal distribution is described as

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma x} exp\left(-\frac{(\ln x-\mu)^2}{2\sigma^2}\right), \tag{B2}$$

where $\mu \in \mathbb{R}$ is the mean and $\sigma \in \mathbb{R}$ the standard deviation ($\sigma > 0$ and $x > 0$).

Gamma Distribution

A Gamma distribution is defined by the probability density function

$$f(x) = \left[\frac{\alpha^\beta}{\Gamma(\beta)}\right] x^{\beta-1} exp(-\alpha x), \tag{B3}$$

where $\alpha \in \mathbb{R}$, $\beta \in \mathbb{R}$ ($\alpha > 0, \beta > 0$ and $x \geq 0$).

APPENDIX C

RELEVANT PROCESSES

Brownian Motion

(See (7)) $$dX_i(t) = \theta \cdot \left(\mu - \lambda \cdot X_i(t)\right) \cdot \left(\frac{X_i(t)}{\mu}\right) dt + \sigma \cdot X_i(t) dW(t)$$

with:

σ: variance of $X_i(t)$, $\sigma > 0$, and

$dW(t)$: a standard Wiener process with zero mean and standard deviation $(dt)^{½}$.

The explicit solution of (7) reads (see, e.g., Dixit and Pindyck (1994, pp. 71, 81)):

$$X_i(t) = X_0 \cdot exp\left[\left(\theta - \frac{\sigma^2}{2}\right) \cdot t + \sigma \cdot W(t)\right]. \quad \text{(C1)}$$

The expected value of X_i is given by $E[X_i(t)] = X_0 \cdot exp(\theta t)$ (C2)

and the variance by $var[X_i(t)] = X_0^2 \cdot exp(2 \cdot \theta \cdot t) \cdot [exp(\sigma^2 \cdot t) - 1]$ (C3)

(see, e.g., Dixit and Pindyck 1994, pp. 71 f.).

Mean-Reverting Geometric Ornstein-Uhlenbeck Process

(See (6)) $$dX_i(t) \propto \frac{X_i(t)}{\mu}$$

The explicit solution is given by Kloeden and Platen (1992):

$$X_i(t) = \frac{exp\left[\left(\theta - \frac{\sigma^2}{2}\right)t + \sigma W(t)\right]}{\frac{1}{X_0} + \theta \int_0^t exp\left[\left(\theta - \frac{\sigma^2}{2}\right)s + \sigma W(t)\right] ds} \quad \text{(C4)}$$

To calculate the probability density of X_i, $f(X_i)$, the stochastic process defined by (6) has the following stationary forward Fokker-Planck equation (Pasquali 2001, p. 169; see also Ewald and Yang 2007, p. 8):

$$\frac{d}{dX_i} \cdot \left[\theta\left(1 - \frac{\lambda}{\mu} X_i\right) X_i f(X_i)\right] - \frac{1}{2} \cdot \frac{d^2}{dX_i^2} \cdot \left[\sigma^2 X_i^2 f(X_i)\right] = 0 \qquad \text{(C5)}$$

As shown by Pasquali (2001, pp. 169 f.) (see also Ewald and Yang 2007, p. 11), this equation has the following solutions for the density function $f(X_i)$:

a) A non-trivial solution exists if and only if $2\theta > \sigma^2$ and it is a Gamma density:

(See (12))
$$f(X_i) = \frac{\left[\left[\frac{\left(\frac{2 \cdot \theta\lambda}{\mu}\right)}{\sigma^2}\right]^{((2(\mu+\lambda))/\sigma^2)-1}\right]}{\Gamma\left(\frac{2\theta}{\sigma^2} - 1\right) X_i^{(2\theta/\sigma^2)-2}} \cdot exp\left[\frac{-2\left(\frac{\theta\lambda}{\mu}\right)}{\sigma^2} X_i\right]$$

In this case, mean and variance are given by:

$$E(X_i) = \frac{\mu}{\lambda} - \frac{\mu\sigma^2}{(2\theta\lambda)} = \left(\frac{\mu}{\lambda}\right) \cdot \left(1 - \frac{\sigma^2}{2\theta}\right) \qquad \text{(C6)}$$

and, respectively,

$$var(X_i) = \frac{\mu^2\sigma^2}{(2\theta\lambda^2)} - \frac{\mu^2\sigma^4}{(4\theta^2\lambda^2)} = \frac{\mu^2\sigma^2}{(2\theta\lambda^2)} \cdot \left(1 - \frac{\sigma^2}{(2\theta)}\right). \qquad \text{(C7)}$$

b) For $\sigma \to 0$ a Dirac Delta distribution results whose mass is concentrated in μ/λ.

c) For $\theta > \sigma^2$, the Gamma density function has a maximum at $X_i = \frac{\mu(\theta - \sigma^2)}{(\theta\lambda)}$ and for $\sigma^2 \in (\theta, 2\theta)$ the maximum is 0.

APPENDIX D

Equation (5) in the text:

$$dX_i(t) = \theta \cdot (\mu - X_i(t))dt + \sigma \cdot X_i(t)dW(t)$$

is derived from the differential equation of Wyard and Bouchaud (2003) (incorporating the variables as defined for this paper):

$\frac{dX_i(t)}{dt} = \theta \cdot \left[\left(\frac{1}{N}\right)\sum_{j=1}^{N} X_j(t) - X_i(t)\right] + \eta_i(t) \cdot X_i(t)$ with $\eta_i(t)$ as a Gaussian random variable.

Using $\frac{1}{N}\sum_{i=1}^{N} X_i\,(t) = \mu(t)$ and $\eta_i(t) = \sigma \cdot \xi(t) = \sigma \cdot dW_t$ with $E\xi(t) = 0$ and $E\xi(t)\xi(t') = \delta(t - t')$ for all $t, t' \geq 0$ and $\xi(t) = \frac{dW_t}{dt} \forall t$ (see Jetschke 1989, pp. 216-218), the differential equation can be written as (5) in the text.

Erklärung

Ich versichere an Eides statt, dass ich die eingereichte Dissertation "*Drivers of Consumer Behavior and Competitive Strategy Outcomes – Plurality of Perspectives, Modeling, and Empirical Evidence*" selbstständig verfasst habe. Andere als die von mir angegebenen Quellen und Hilfsmittel habe ich nicht verwendet. Alle wörtlich oder sinngemäß den Schriften anderer Autoren entnommenen Stellen habe ich durch Angabe der entsprechenden Quellen kenntlich gemacht. Weiterhin versichere ich, dass diese Dissertation nicht bereits anderweitig als Prüfungsarbeit vorgelegt wurde.

Jan Piening

Münster, den 30. Januar 2013