Effects of Consumer Learning and Channel Choice in Loyalty Programs

Completed Research Paper

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Abstract

Based on a large-scale, unique longitudinal dataset comprising more than four million individual transactions, we study linkages between consumer learning, channel choice, and purchase behavior. We focus on online versus traditional over the counter channels. First, we investigate how the occurrence of consumer 'learning' is related to 'unlearning' in loyalty programs, and how (un)learning depends on the chosen channel. Second, we study how (un)learning effects, along with other contingent factors, impact customer loyalty, and explore whether the strength and/or significance of effects change over time. Hypotheses are tested in the context of two-part pricing schemes in travel services that are particularly intended to create loyalty, and offer a rare opportunity for an objective assessment of learning effects. Results show that (un)learning, as well as channel choice, and pricing issues, are significantly associated with contract cancelation. We provide managerial implications that help retailers re-develop, communicate and fine-tune loyalty programs more effectively.

Keywords: learning, electronic commerce, consumer behavior

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 environments and decreasing switching costs make customers ever more difficult to retain (Srinivasan et al. 2002).

Under these challenging conditions, firms must allocate their resources effectively within and across distribution channels to create sustainable customer relationships (Bart et al. 2005). 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 linkages between customer characteristics and the use of online purchase systems versus traditional channels (Brown and Dant 2009; Hitt and Frei 2002; Reinartz et al. 2004; Wallace et al. 2004), and the question of how different channels are related to consumer behavior and customer loyalty remains surprisingly unanswered to date (Brown and Dant 2009; Hitt and Frei 2002; Homburg et al. 2002; Reinartz et al. 2004; Wallace et al. 2004).
Across distribution channels, customer loyalty is a critical goal for firms (Jacoby and Chestnut 1978; Laroche et al. 2005; Wallace et al. 2004). Loyal customers buy more often, are willing to pay higher prices, and generate positive word of mouth (Oliver 1997; Reichheld 1993; Zeithaml et al. 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 et al. (2000), Keh and Lee (2006), Leenheer et al. (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 loyalty programs do not produce the results desired by the firm. Still, insights into the responsiveness across different customer segments and their buying behavior as well as effects of loyalty programs in different channels are unfortunately scarce (Gommans et al. 2001; Ramsay 2010; Shankar et al. 2003). Likewise, the role of consumer learning in connection with loyalty programs and channel choice remains completely unexplored. In sum, research has not adequately considered market-level responses to different channels and how they relate to consumer learning and buying behavior, 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 consumer learning, channel choice, and purchase behavior. Hypotheses are tested in the context of two-part pricing schemes (loyalty cards) in services, as these are intended to create customer loyalty, and offer a rare opportunity for a comparatively objective assessment of learning effects. We focus on the German rail travel sector, where consumers can choose to buy loyalty cards that allow them certain discounts on future fares. First, we investigate how consumer learning in loyalty programs develops, also depending on the chosen online versus traditional over the counter channel (Study I). Second, we study how these learning effects, along with other contingent factors, impact customer loyalty, and we explore whether the strength and/or significance of these effects change over the course of time. We contribute to the e-tailing literature by offering theoretical and managerial implications.

**Conceptual Background**

*Learning Effects in Loyalty Programs.* In many industries today, customers are confronted with two-part pricing schemes, which are frequently used in the context of customer loyalty programs. Under such schemes, consumers are supposed to choose the tariff most appropriate to their subsequent usage behavior. For example, consumers may choose to pay per use if they expect they will make limited use of the respective service; in contrast, if they expect to use that service much, they may opt for a flat rate fee with unlimited access – to pay less than what they would have to pay if choosing to pay per use. Here, obviously, consumers face the risk of selection bias, i.e. choosing a ‘wrong’ tariff for their actual consumption.

Following the microeconomic model of expected utility maximization (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” offers becomes complicated and time-consuming. Consumers’ rationality in forming preferences is further 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: 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 an “optimal” purchase decision in the following, other behaviors are considered as “non-optimal” (“beyond optimal” for over-usage, “suboptimal” for under-usage).

Nunes (2000) explains how customers integrate subsequent usage expectations into the decision process
when choosing between tariffs. Consumers usually compare the subjective likelihood of using more than the break-even volume with the subjective likelihood of using less. He finds that customers habitually overestimate the likelihood of using the service, and thus they go wrong in tariff choice. Other examples of studies examining flat rate biases are Thaler (1999), Della Vigna and Malmendier (2006), Lambrecht and Skiera (2006), Goettler and Clay 2011, and Schmale, Ehrmann, and Dilger (2013).

In fact, a large literature in industrial organization analyzes the profit-maximizing contract design (Tirole 1988). A standard assumption in this literature is that consumers have rational expectations about their future consumption frequency and choose the utility-maximizing contract. The analysis of consumer behavior is just the first step toward a better understanding of industries where consumers display nonstandard preferences or beliefs. Profit-maximizing firms should respond to the nonstandard features of consumer behavior in their contract design. This is the central theme of the growing literature on behavioral industrial organization (Della Vigna and Malmendier 2006).

However, customers may learn over time to correctly use their loyalty cards. That means, having chosen a non-optimal tariff (either over-using or under-using the chosen card) previously, consumers may re-evaluate their tariff choice over time and potentially understand that they need to switch to a different contract that saves them more money than the currently chosen tariff. This is what we consider as a “learning effect” in this context. Yet, customers can also unlearn choosing correct tariffs (despite the fact that there could always be unexpected events that increase or decrease usage unexpectedly, so that ex ante ‘perfect’ choices turn out imperfect ex post, which however, we expect would be more of an exception than the rule). That means consumers may wrongly decide to switch to another tariff, although they actually already had the tariff best for them. This is what we consider as an “unlearning” effect, i.e. moving from an optimal choice to a worse solution. For example, Narayanan, Chintagunta, and Miravete (2007) explore the usage of local telephone services and find that customers learn about their own usage patterns and switch plans to save costs. Likewise in our context, customers make decisions under uncertainty, and end up with making choices that are potentially non-optimal.

**Channel Choice.** 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). Yet, there is little systematic knowledge about consumers preferences for Internet versus traditional channels (Gommans et al. 2001; Ramsay 2010; Shankar et al. 2003). 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 et al. 2007). 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, yet, Berthon et al. (1999), Laroche et al. (2005), and Thakor et al. (2004) also discuss the functionality of the Internet in offering a plethora of information to consumers who are willing to search for it.

**Customer Loyalty.** Loyalty has been extensively studied based on various definitions (Day 1969; Jacoby and Chestnut 1978; Keh and Lee 2006; Oliver 1997). In line with Srinivasan et al. (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 (also, due to data limitations concerning psychological aspects of loyalty). Customer loyalty is of extreme interest to firms as even a small decrease in customer loyalty can make a large difference for earnings (Wallace et al. 2004), and becomes ever more important as the Internet fuels retailing competition and reduces switching costs.

Against this background, our research questions are:

**Study I:** How is the occurrence of consumer learning related to unlearning in loyalty programs, and how does (un)learning depend on channel choice?

**Study II:** How do consumer-inherent learning effects vs. other contingent factors impact customer loyalty, and how do effects change over the course of time (i.e. program membership duration)?

**Data Acquisition and Key Variables**

Data. 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”. The data
include more than four million transactions conducted with any of the 800,000 BahnCards in the sample. DB customers can choose between three contracts: the BahnCard25 (BC25), the BahnCard50 (BC50) and the BahnCard100 (BC100). 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.¹ We concentrate on second class BahnCards only to ensure contracts are comparable using data from December 2002 through July 2008 (due to the introduction of a new pricing scheme in late 2002). 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.

Variables. counter1, ..., counter5 and internet1, ..., internet5, define whether cards and subsequent tickets were bought from the counter or via the Internet in the respective year of usage (i.e., ‘1’ denotes ‘year 1’, ‘2’ denotes ‘year 2’ asf.) The dummy variable cancel1, ..., cancel5 indicates whether a customer terminated the card contract in the respective year of usage, the variable price1, ..., price5 determine the price of the particular BahnCard in its respective year of usage. We also consider the contract duration in years, demographical information sex (1 – male, 0 – female) and age in years in subsequent analyses.

To assess the optimality of customers’ contract choices ex post, we set up the following framework of BahnCard choice and usage: Let \( (L, \alpha) \) be a contract where \( L_i \) stands for different fixed fees that result in different variable fee rebates \( \alpha \) on ticket price \( p \). This contract enables customers to use a train for a fee \( \alpha \) 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 \( \alpha \) 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

\[
L_{25} + 0.75v \geq L_{50} + 0.5v \geq L_{100}
\]

and thus \( v_{50} = L_{25}/0.25 \).

\[
v_{100} = (L_{100} - L_{50})/0.5.
\]

The binary parameters suboptimal and beyond optimal are calculated according to this scheme.

For the learning variable, a change from suboptimal or beyond optimal BahnCard usage towards an optimal usage from one year to another constitutes ‘learning’, marked 1 for the variable ‘learn’ (and 0 otherwise). Accordingly, a reverse change (from optimal to beyond or suboptimal usage) is denoted by 1 for the variable ‘unlearn’ (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). We also control for customers’ demographic characteristics like sex and age as well as for the price paid for a loyalty card as stated in the following analyses.

**Study I: Consumer (Un)Learning and Channel Choice**

Placing emphasis on ‘unlearning’ as an essential, yet largely neglected, driver of consumers’ purchase behavior complements the large body of work that emphasizes learning effects (see also, Baum and Dahlin 2007; Chuang and Baum 2003; Denrell 2003). Simultaneously, as we redirect the focus from the ‘learning from success perspective’, we contribute to the development of the emerging experiential learning-from-failure perspective (Haunschild and Rhee 2004; Haunschild and Sullivan 2002; Kim 2000; Miner et al. 1999). This is important as learning to optimally use a loyalty card might be driven by different underlying factors than unlearning to use that card optimally. That is, e.g., usage experience, willingness to adopt, rational mind-set etc. might increase learning, whereas e.g., exaggerated risk-

¹ We do not study the BC100 segment as we cannot trace the customers’ travel behavior due to the flat-rate tariff.
aversion, over-estimation bias, irrationality, may drive unlearning. In that case, rather than following an inverse form, the structure of the learning curve would differ from the structure of the unlearning curve.

Further, 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 learning effects may not necessarily be expected. Here, Internet usage has been found to vary systemically 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, as older consumers tend to perceive online purchasing as more risky, more time-consuming and more difficult than buying via traditional channels (Yoon 2002; Hitt and Frei 2002; Laroche et al. 2005; Miyazaki and Fernandez 2001; Weathers et al. 2007). However, reluctance to Internet channels will at times result in voluntarily relinquishing valuable information that could be gained by searching online, e.g., on tariff arrangements and additional options. That is, given the functionality of the Internet in offering a plethora of information to consumers who are willing to search for it, vs. offline points of sale where information is handed out at the discretion of the sales agent, it may well be that (un)learning varies by channel choice, i.e. by buying online vs. over the counter. Therefore:

$H_{A1}$: The structure of the average learning curve for loyalty card purchases differs from the structure of the average unlearning curve.

$H_{A2}$: The structure of the (un)learning curve for loyalty card purchases varies across online and traditional over the counter channels.

Method

We analyze how the share of customers who learn and of those who unlearn develops during their respective membership 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’. Of course, we treat BC25 and BC50 customers separately. Next, we use an unpaired, two-sample mean-comparison test (t-test) to compare the values of the each year in online and offline channels.

Analysis and Results

In the BC25 segment, the learning rate slightly decreases over time, although it remains on a similar level throughout membership duration (i.e. concerning the renewal of the card in years subsequent to the initial year of purchase). We observe an average share of learners of 8.90 % in the second usage period in comparison to the first, which declines to a share of 6.98 % at the end of the sixth year of usage in comparison to the fifth. The corresponding test results ($M_{Learn1}$ vs. $M_{Learn5}$; 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 12.07 %. This value decreases until the end of the fourth usage period (9.10 %) and grows again to 10.31 % in the end of the sixth usage period. The corresponding t-test results are: ($M_{Unlearn1}$ = .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 the learning and unlearning curves, providing direct support for $H_{A1}$.

Focusing on channel choice, for online customers, the learning rate turns out to be u-shaped (yet on a relatively stable level), whereas the t-tests reveal a decreasing unlearning rate over membership duration. The share of learners decreases from 10.14 % to 8.95 % at the end of contract year four and increases to 10.00 % 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 % to 9.80 %. The corresponding t-tests provide ($M_{unlearn1}$ = .1551345 vs. $M_{unlearn2}$ = .1244877; t = 7.3192; p < 0.0001), ($M_{unlearn2}$ = .1244877 vs. $M_{unlearn3}$ = .1079365; t
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= 3.4415; \( p < 0.001 \), (\( M_{\text{Unlearn2}} = .1079365 \) vs. \( M_{\text{Unlearn3}} = .0980493; t = 1.6150; p < 0.05 \). For over the counter customers, both learning (6.32 % in the first year, 5.95 % in the final year) and unlearning (9.03 % vs. 9.47 %) curves remain relatively stable, but at a lower level than for online customers, over time. Thus again, we detect different structures of learning and unlearning curves, and the curve progression depends on customers’ channel choices. (For both hypotheses, we obtain similar results for the BC50 customers, which are not shown due to space restraints but are available from the authors.)

Thus, the structure of the average learning curve differs from the structure of the average unlearning curve, and the structure of learning curves as well as of the unlearning curves varies across online and offline distribution, providing full support for the hypotheses \( H_{1a} \) and \( H_{1b} \).

Discussion

The results of Study I illustrate that learning, in terms of the adoption of ex post optimal usage behavior, is connected to the buying context in term of online vs. offline purchasing. Apparently, online customers show more ‘variation’ in their learning activity, as well as their unlearning activity, as compared to over the counter customers who do not show much variation in (un)learning over time. Interestingly, in both cases, the share of unlearners almost always exceeds the share of learners. This could mean that consumers become indifferent towards realistically assessing (renewed) purchase options pretty fast, or hint at an overconfidence bias after initial product experience that makes consumers sloppy in their future planning.

A second interesting aspect concerning the structure of learning curves is that although a learning customer can conceptually be regarded as the opposite of an unlearning customer, learning and unlearning curves are not described by an inverse relationship. As explained above, the reason might be that there are different relevant underlying drivers that facilitate learning in comparison to making customers unlearn.

Still, one must note that about 75-85 % of customers do not exhibit any learning or unlearning tendencies in the respective years of usage at all. These customers keep on using their BahnCard in the same way as the preceding year – either optimally or non-optimally.

Study II: Determinants of Cancelation Behavior

Research has identified various determinants of customers’ loyalty and disloyalty in terms of contract cancelation. However, the role of learning has not yet been considered in a loyalty program context. Yet, Iyengar, Ansari, and Gupta (2007) conduct policy experiments to capture effects of customer learning, pricing, and service quality on customer lifetime value. They find that learning can in fact provide for a firm-customer win-win situation, as they identify the change in retention rate with and without learning as a key driver of customer value. Then, if learning customers turn out to be more loyal to the firm, we extent the approach to unlearning as a loyalty-decreasing effect that likely results in card cancelation:

\[ H_{2a}: \] Learning effects decrease the he likelihood of cancelation, whereas unlearning effects increase the likelihood of cancelation.

\[ H_{2b}: \] The retention rate is higher (lower) for learners (unlearners) than for ‘non-learners’.

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 et al. 2001; Ramsay 2010; Shankar et al. 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

\[ In the BC50 context, we find stronger learning effects, and lower ‘unlearning’, in general, compared with BC25. Besides, Internet buyers again display a u-shaped learning rate, and they learn ‘more’ on average per year than counter customers; and Internet buyers ‘unlearn’ at a decreasing rate, and unlearn slightly less than counter customers. \]
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; McAlistier and Pessemier 1982; Ramsay 2010; Ratner et
al. 1999; Tang and Chin 2007). On the contrary, some scholars claim that customers could even be more
loyal online (Shankar et al. 2003), whereas others expect little differences overall (Walsh et al. 2010).

Accordingly, we assume that the ‘contact point’ from which customers choose to buy their tickets during
program membership may have an effect on subsequent cancelation of the overall card. That is, customers
choosing the Internet channel may for example, feel able to decide about contract renewal whenever
convenient and may thus take their time to make balanced decisions about contract renewal, whereas
customers focused on counter transactions may feel more of a need to terminate the contract to be ‘on the
safe side’ in case they do not come to see an agent in due time again. Besides, whereas Internet purchases
are convenient, counter customers may get frustrated with circumstantial factors of ticket purchase, e.g.,
with standing in line long time or unhelpful staff, and thus tend to look for alternative transportation
arrangements. Hence, channel choice may affect cancelations:

H₃a: Counter ticket purchases during membership duration increase the likelihood of
the decision to cancel a loyalty card.

H₃b: Internet ticket purchases during membership duration decrease the likelihood of
the decision to cancel a loyalty card.

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. Accordingly, the past, and particularly the current optimality of
usage of a loyalty card may be a key driver for refraining from vs. deciding on contract cancelation:

H₄a: Current optimality of usage of a loyalty card decreases contract cancelation.

H₄b: Past optimality of usage of a loyalty card decreases contract cancelation.

Moreover, although loyalty is studied extensively in the literature, its relation to pricing strategies
is not well understood (Allender and Richards 2012). Yet, pricing should affect loyalty behavior as if services are
offered at a high price, they may not make customers turn away, but in contrast, risk aversion may drive
consumers to stick with a firm whose services have proven satisfactory. However, still, many consumers
may seek out alternative travel options, if they feel prices are reaching a sensible limit. Thus, we assume
that the annual repurchase price of a BahnCard (i.e. for contract renewal) impacts cancelation.

Besides, based on the concept of price fairness (e.g. Bolton, Warlop, and Alba 2003) where consumers
draw a comparison of a price with a pertinent standard, reference, or norm, we expect that apart from the
overall price, also the difference between the previous year’s price and the renewed contract card’s price
will have an effect. Xia, Monroe, and Cox (2004) observe that if the perceived price discrepancy between
two transactions is high, a high degree of transaction similarity (as in the case of contract renewal) leads
to the perception of high price unfairness, so that customers may switch to alternative service offerings:

H₅a: A high subsequent annual repurchase price of a loyalty card increases contract cancelation.

H₅b: A high difference between previous price and the subsequent annual repurchase price of the
card increases contract cancelation.

Taking a dynamic perspective, Bingham and Davis (2012) develop a concept of learning for organizational
processes and find that learning sequences exist. We apply the idea of these learning sequences to
customer behavior. That is, learning processes during membership duration (resulting from e.g.,
experimental, trial-and-error, vicarious learning, or learning from external advice) may emerge in
sequences, so that the factors under study can vary in their importance and effect on cancelation behavior
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over time:

H6: Effects do not remain stable over time.

Method

We calculate collective annual cancelation rates of all customers (either, BC25 and BC50; for learning and unlearning customers) being in their nth year of BahnCard usage. For the comparison of cancelation rates between the different usage periods, we use unpaired, two-sample mean-comparison tests (t-tests) (H_{2ab}). To explore linkages between (un)learning, channel choice, pricing, usage behavior and cancelation events, we use chi-square tests of independence for each year of BahnCard contract duration and show which parameters can be statistically associated with contract cancelation activities (H_{3a,5b}).

For H6, we study cancelation events applying a sequential logit model. Our aim is to identify changes in the direction and magnitude of effects during program membership. We employ the variables described in section 2, i.e. learn, counter, usage (in terms of suboptimal and beyond optimal usage), sex, age, we also use the price (in €) for the subsequent contract renewal and the price difference between previous price and the subsequent repurchase price, each 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 cancelation (or not) events at the end of each annual BahnCard period during membership duration, using the train data. This approach can be formalized as follows:

\[
P(\text{cancel}_i = 1) = \frac{1}{1 + e^{-z_i}}, \text{ where } i \text{ defines the end of the respective contract year and}
\]

\[
z_i = \beta_0 + \beta_1 \times \text{usage}_{i} + \beta_2 \times \text{age}_{i} + \beta_3 \times \text{sex} + \beta_4 \times \text{price}_i \quad \text{(for } i = 1\text{)}
\]

\[
z_i = \beta_0 + \beta_1 \times \text{usage}_{i} + (\beta_2 \times \text{learn}_1 + \cdots + \beta_{i-1} \times \text{learn}_{i-1}) + \beta_{i+1} \times \text{age}_{i} + \beta_{i+2} \times \text{sex} + \beta_{i+3} \times \text{counter}_{i} + \beta_{i+4} \times \text{price}_i \quad \text{(for } i > 1\text{)}
\]

Subsequently, we score the test dataset with the obtained parameter estimates to validate our model and to verify result robustness, separately for the BC25 and BC50 data.

Results

Concerning the assumption that learning effects influence the cancelation of a BahnCard (H_{2a}), they do have an impact on cancelation, and 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_{25} = 54.1510, p < .001, respectively; BC50: Pearson \chi^2_{50} = 44.9323, p < .01, respectively). ‘Late’ effects, i.e. (un)learning after more than three years of contract duration, play a minor role in determining cancelation events. In sum, H_{2a} is largely supported.

We find that the retention rate is significantly higher for learners than for ‘non-learners’ in both low- and high-price contexts. Results are (M_{Learn} = .1027316 vs. M_{NoLearn} = .1644791; t = -6.5829; p < 0.001), (M_{Learn} = .0527363 vs. M_{NoLearn} = .1244789; t = -6.7364; p < 0.001), (M_{Learn} = .0739687 vs. M_{NoLearn} = .1013167; t = -2.3192; p < 0.01), (M_{Learn} = .0401891 vs. M_{NoLearn} = .0881657; t = -2.3192; p < 0.01) for the BC25 customers. For the BC50 customer segment, results are (M_{Learn} = .0908669 vs. M_{NoLearn} = .1634246; t = -8.7662; p < 0.0001). (M_{Learn} = .0671937 vs. M_{NoLearn} = .1313252; t = -6.5308; p < 0.001), (M_{Learn} =

\footnote{Because of data limitations, we treat all cases with n≤5 as data for the final year was not fully available.}

\footnote{\chi^2_{i+1} \text{ represents the Pearson chi-square value associated with a learning effect after } i+1 \text{ years of contract and a cancelation event after } j \text{ years.}
Accordingly, Internet ticket purchases decrease the cancelation risk for card contracts, supporting a highly significant positive connection to customer cancelation (Pearson $R = .1833273$ vs. $M_{NoUnlearn} = .1644791$; $t = 2.4344; p < 0.01$). Apart from these findings, we cannot establish significant differences between cancelation rates of unlearners and ‘non-learners’ (not even at the 0.1-level). In sum, we find full support for hypothesis H$_{ab}$ in the high-prize, i.e. BC50, context and mixed support in the low-price BC25 context.

The examination of linkages between channel choice and contract cancelation reveals the following results: As expected, and supporting H$_{3a}$, we find that counter ticket purchases are associated with cancelation behavior for both low- and high-price contexts in every year of contract duration, meaning cancelation is higher if ticket purchase is pursued via traditional counter channels (BC25 (Pearson $R = .14527$ vs. $M_{NoUnlearn} = .1345108$; $t = 9.6651; p < 0.0001$) and BC50 (Pearson $R = .27191$ 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. $M_{NoUnlearn} = .1644791$; $t = 2.4344; p < 0.01$). Apart from these findings, we cannot establish significant differences between cancelation rates of unlearners and ‘non-learners’ (not even at the 0.1-level). In sum, we find full support for hypothesis H$_{ab}$ in the high-prize, i.e. BC50, context and mixed support in the low-price BC25 context.

Next, the chi-square tests of independence reveal that the optimality of usage of a BahnCard, in terms of a suboptimal, beyond optimal and optimal usage, is associated with card cancelation (as intuitively expected). Particularly, the optimality of usage of the current BahnCard turns out to be connected to customer cancelation for both low- and high-prize contexts in every year of usage (BC25 (Pearson $R = .14527$ vs. $M_{NoUnlearn} = .1345108$; $t = 9.6651; p < 0.0001$) and BC50 (Pearson $R = .27191$ vs. $M_{NoUnlearn} = .1315108$; $t = 3.1877; p < 0.001$). Concerning past optimality of usage, this effect is mixed. Several elapsed contract periods exhibit statistically significant connections to cancelation events, but particularly early periods of relatively long contract durations do not (p > 0.05). In sum, the hypotheses H$_{3a}$ and H$_{ab}$ are mostly supported.

Testing our hypotheses on pricing leads to clear results: both hypotheses (H$_{a,b}$) are fully supported. The subsequent annual repurchase price of a loyalty card plays a highly significant role for cancelation in any year for BC25 customers (Pearson $R = .14527$ vs. $M_{NoUnlearn} = .1345108$; $t = 9.6651; p < 0.0001$) and BC50 customers (Pearson $R = .27191$ vs. $M_{NoUnlearn} = .1315108$; $t = 3.1877; p < .001$). Here, studying price differences between the previous (i.e. the current) and the subsequent card, the previously price paid indeed seems to serve as a kind of reference point. For the BC25 customers, the subsequent annual repurchase price in any year of usage is independent from customer cancelation when this price is below the price paid for the previous BahnCard (at 0.1-level). Once the subsequent price exceeds the price of the previous BahnCard, we find a highly significant positive connection to customer cancelation (Pearson $R = .14527$ vs. $M_{NoUnlearn} = .1345108$; $t = 9.6651; p < 0.0001$). Overall, the findings also apply to the BC50 customers (Pearson $R = .27191$ vs. $M_{NoUnlearn} = .1315108$; $t = 3.1877; p < .001$), but the subsequent annual repurchase price seems to be less important: up to contract year three a high subsequent repurchase price leads to cancelation ($R = .14451; p < .001$), yet even, if it is below the previous card’s price. After that, prices are statistically not associated to customer cancelation (p > .5).

As regards H6, learning (and unlearning) effects do have an impact on contract cancelation, but effect directions and magnitudes vary over time, giving full support to hypothesis H$_6$. For example, in case of the BC25 customers, unlearning exhibits a significant positive influence on cancelation (i.e. increases cancelations) in the first two years of contract duration, yet thereafter is associated with a decreased probability of terminating the contract. Generally, unlearning effects seem to be relevant for cancelation events predominantly in the early contract stages. The direction of learning effects changes in early stages, but counter-intuitively tends to exhibit a positive connection to the cancelation probability in the low-price segment. In contrast, for the BC50 customers learning effects tend to decrease the probability of
cancelation (as expected). Unlearning effects always increase the cancelation risk (also as expected).

In summary, learning effects tend to support 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, yet seems to be positively associated with cancelation probabilities of contracts that have run longer than two years. Counter purchase significantly increases the probability of a contract cancelation throughout contract periods. Concerning the variable optimality of usage, the category describing suboptimal usage behavior proves to be statistically positively significant (p < .001) in the first three years of contract duration of BC25 customers. Among the BC50 customers this parameter significantly increases cancelation in any year of contract duration. Beyond optimal usage tends to reduce the risk of cancelation, although not always (BC25) or rather not (except 2nd year, BC50) in any significant way. As regards the impact of BahnCard prices on contract cancelation, for both BC25 and BC50, the previous price paid for the card in any year of program membership has a significant influence on cancelation.6

Exemplary regression results for years 1 and 4 of contract duration are displayed in tables 1a,b (BC25) and 2a,b (BC50).

**Train data**

| Predictor variable | Coef.       | Std. Err. | Z     | P>|Z|  | [95% Conf. Interval] |
|--------------------|-------------|-----------|-------|------|---------------------|
| 0                   | 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| -.10221801 -.0172642 |
| Counter ***        | .4978051    | .0452635  | 11.00 | 0.000| .4090902 .58652    |
| Previous Price ***| -.0295995   | .0018707  | -15.82| 0.000| -.0332659 -.025933 |
| _cons              | .3276857    | .1063901  | 3.08  | 0.002| .19165 .5362064    |

Number of obs = 20732 LR chi2(7) = 763.91 Prob > chi2 = 0.0000 Pseudo R2 = 0.1395 Precision 0.87 Recall 0.87

**Test data**

| Predictor variable | Coef.       | Std. Err. | Z     | P>|Z|  | [95% Conf. Interval] |
|--------------------|-------------|-----------|-------|------|---------------------|
| 0                   | 0 (base outcome) |           |       |      |                     |
| 1 Score1 ***       | -5.298325   | .4444564  | -11.92| 0.000| -6.169462 -.427189 |

---

6 As regards the controls, customer age significantly contributes to the explanation of contract cancelation in both low- and high-prize contexts and in each year of contract duration. The rule is ‘the younger, the higher the affinity to cancelation’. Sex only proves to significantly explain cancelation 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.
### Table 1a. BC25 – Logistic Regression Results Year 1

#### Train data

| Predictor variable: | Coef.  | Std. Err. | Z    | P>|Z|     | [95% Conf.] | Interval      |
|---------------------|--------|-----------|------|---------|------------|--------------|
| 0                   |        | (base outcome) |      |         |            |              |
| 1                   |        | Usage4 ** | 1.07016 | .3754394 | 2.85       | 0.004        | .3343122     | 1.806008    |
|                     |        | Sub_opt ** | .2507131 | .4378062 | 0.57       | 0.567        | -.6073714    | 1.108798    |
|                     |        | Byo_opt | .2507131 | .4378062 | 0.57       | 0.567        | -.6073714    | 1.108798    |
|                     |        | Learn1 | .3515801 | .2374953 | -1.48      | 0.039        | -.8170623    | .1139021    |
|                     |        | Learn2  | .0009643 | .1340184 | 0.01       | 0.994        | -.2617069    | .2635355    |
|                     |        | Learn3  | .0742739 | .3166385 | 0.23       | 0.815        | -.5463262    | .694874     |
|                     |        | 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        | .0791644     | .5463071    |
|                     |        | Previous Price *** | -.0544689 | .0102242 | -5.33      | 0.000        | -.0745079    | .0344298    |
|                     |        | Price Difference ***  | -.5623422 | .0561347 | -10.02     | 0.000        | -.6723641    | -.4523202   |
| _cons               | 2.76331 | .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

Precision 0.89  Recall 0.81

### Test data

| Predictor variable: | Coef.  | Std. Err. | Z    | P>|Z|     | [95% Conf.] | Interval      |
|---------------------|--------|-----------|------|---------|------------|--------------|
| 0                   |        | (base outcome) |      |         |            |              |

Number of obs = 6797  LR chi2(7) = 305.60  Prob > chi2 = 0.0000  Pseudo R2 = 0.1702

Precision 0.90  Recall 0.82
Consumers’ Learning Effects and Channel Choice

| 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 |
| Precision 0.89 | Recall 0.77 |

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

Table 1b. BC25 – Logistic Regression Results Year 4

| Train data |

| Predictor variable: | 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 | 2.203083  | .0725343 |
| Age ***            | -.0239629 | .0009613 | -24.93 | 0.000 | -.025847  | .0220787 |
| Counter ***        | .5254999 | .0382934 | 13.72 | 0.000 | 4.504462  | .605536  |
| Previous Price ***| .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 |
| Precision 0.79 | Recall 0.77 |

Test data

| Predictor variable: | Coef. | Std. Err. | Z   | P>|Z| | [95% Conf. Interval] |
|--------------------|-------|-----------|-----|------|---------------------|
| 0 (base outcome)   |       |           |     |      |                     |
| 1                  |       |           |     |      |                     |
| Score1 ***         | -5.494056 | .3921509 | -14.01 | 0.000 | -6.262567 | -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 |
| Precision 0.90 | Recall 0.80 |

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

Table 2a. BC50 – Logistic Regression Results Year 1

Train data
### Consumers’ Learning Effects and Channel Choice

#### Table 2b. BC50 – Logistic Regression Results Year 4

| Predictor Variable | Coef.       | Std. Err.  | Z     | P>|Z| | [95% Conf.]   | Interval |
|--------------------|-------------|------------|-------|------|----------------|----------|
| 0                  | (base outcome) |            |       |      |                |          |
| 1                  |             |            |       |      |                |          |
|                       | **Usage4**  |            |       |      |                |          |
|                       | **Sub_opt***| 1.017072   | .156268 | 6.51 | 0.000          | .711392  | 1.323952   |
|                       | **Byo_opt** | -6.089505  | 1.039108 | -0.59 | 0.558          | -2.645565 | 1.427663   |
|                       | **Learn1**  | .120166    | .156163 | 0.77  | 0.442          | -1.859093 | .4262418   |
|                       | **Unlearn** | .091643    | .133974 | 0.68  | 0.494          | -1.709397 | .3542264   |
|                       | **Learn2**  | -0.085732  | .184297 | -0.47 | 0.642          | .4469481  | .2754831   |
|                       | **Unlearn** | .206134    | .146546 | 1.41  | 0.160          | -.0810834 | .4933525   |
|                       | **Learn3**  | -1.127474  | .236963 | -0.54 | 0.591          | -1.591912 | .336963    |
|                       | **Unlearn†**| .1698037   | .150539 | 1.13  | 0.059          | -1.252483 | .4648557   |
|                       | **Sex**     | -2.112289  | .082162 | -2.58 | 0.010          | -1.473356 | -.0512423  |
|                       | **Age***    | -0.010839  | .002032 | -5.33 | 0.000          | -.0148231 | -.0068554  |
|                       | **Counter***| .343861    | .100314 | 3.43  | 0.001          | -.1472482 | .5404743   |
|                       | **Previous Price*** | -0.0067795 | .0015135 | -4.48 | 0.000          | -.009746  | -.0038131  |
|                       | **Price Difference*** | .0053729 | .0014224 | 3.78 | 0.000          | .0025852  | .0081607   |
|                       | _cons       | -1.842428  | .214708 | -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    Precision 0.89    Recall 0.77

#### Test data

| Predictor Variable | 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    Precision 0.79    Recall 0.77

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

Study II connects (un)learning, channel choice, pricing, optimality of usage, and cancelation decisions in loyalty programs. Learning effects do have an impact on cancelation 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 complementarily, unlearning increases the cancelation of loyalty cards, although the latter effect holds more for the high-price context. However, the significance of effects changes over time, that is, (un)learning affects decisions to cancel more strongly in ‘early’ years of membership. This draws additional attention to the importance of learning, as well as unlearning, effects to understand customer behavior in loyalty programs and accordingly, design programs in such a way that is advantageous to the firm’s objective.

Relatedly, the findings concerning channel choice carry essential implications for development and coordination of different distribution channels. In our case, learning and unlearning varies by channel choice. Although consumers self-select into their preferred channel, firms may decide to help them achieve learning effects in order to increase customer loyalty. Here, making informed purchase decisions may need different forms of support at different points in time. Our results show that using the Internet channel is negatively related to card cancelations. This could imply that online buyers make more informed decisions than counter customers. In consequence, online customers turn out to be more loyal than counter customers.

Besides, the optimality of usage of the current BahnCard appears to be connected to customer cancelation for both low- and high-prize contexts in any year of usage (with non-optimal usage increasing cancelations, as expected), whereas effects of past optimality of usage are mixed.

The implementation of appropriate pricing strategies for contract renewal is also a crucial factor for controlling customer churn. Given the difference in results for the high-price (BC50) and the low-price (BC25) segments, it appears that higher prices at least induce more careful customer planning behavior that may ex post turn out as being optimal. Another outcome is the following: the higher the price of contract renewal, the higher is the risk of a contract cancelation in the low-price segment, and the higher the risk in the high-price segment. Accordingly, firms offering loyalty cards in two-part tariff-systems may want set the initial prices relatively high and in the following contract periods reduce it or keep their prices stable.

General Discussion

First, learning versus unlearning of loyalty card usage in two-part pricing systems is not characterized by an inverse relationship, as one might expect, but eventually depends on different underlying drivers. Second, realizing learning as well as unlearning effects is centrally connected to channel choice (Study I). Third, learning and unlearning, as well as channel choice or pricing issues, are significantly associated with contract cancelation in loyalty programs (Study II). Understanding effect changes over time and by pricing context (i.e. BC25 vs. BC50) can be helpful for firms to re-develop, communicate and fine-tune their loyalty card programs. Thereby, a better understanding of the nature of (un)learning and its interrelationship with pricing and usage can contribute to a more successful implementation of loyalty programs. Table 3 summarizes the main findings.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Result</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a</td>
<td>The structure of the average learning curve for loyalty card purchases differs from the structure of the average unlearning curve.</td>
<td>✓</td>
</tr>
<tr>
<td>1b</td>
<td>The structure of the (un)learning curve for loyalty card purchases varies across online and traditional over the counter channels.</td>
<td>✓</td>
</tr>
<tr>
<td>2a</td>
<td>Learning effects decrease the likelihood of cancelation, whereas unlearning effects</td>
<td>✓</td>
</tr>
</tbody>
</table>
Table 3. Summary of Hypotheses and Results

### Theoretical Implications

We provide several contributions. First, few studies have explicitly focused on customer heterogeneity and how it relates to online versus offline purchasing (Hitt and Frei 2002; Tsai and Lee 2009). We do so, based on studying customers’ heterogeneous learning potential vs. unlearning potential in Internet vs. counter distribution. Second, 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 et al. 1999; Hitt and Frei 2002; Lee 1998; Shapiro and Varian 1998). We explicitly hypothesize that learning potential varies by channel choice, both for initial as well as for subsequent purchase decisions, due to consumers’ self-selection into either channel and the amount and form of information offered in each.

Third, we complement recent literature on choice and consumption in multi-part pricing schemes (Ascarza, Lambrecht, and Vilcassim 2012; Bagh and Bhargava 2007; Grubb 2009; Grubb and Osborne 2011; Iyengar, Ansari, and Gupta 2007; Jensen 2006), which has largely neglected linkages between (un)learning effects in tariff schemes and customer retention. Thus, we integrate customer learning and unlearning into this context, and highlight their temporal effects based on a longitudinal approach.

Fourth, although customer satisfaction with purchase decisions is extensively studied, decision quality in terms of optimality of usage is not, although it complements satisfaction research by providing a more objective and less volatile assessment of purchase advantageousness. Two-part pricing contracts offer a prime opportunity for such objective assessments. Thereby, we add to the literature investigating multichannel distribution, as a better understanding of the linkages between learning effects, usage, pricing, and loyalty behavior is important for firms that combine distribution channels, and for allocating...
resources effectively across and within channels.

**Methodological Implications**

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. To date, few studies investigate determinants of consumer responsiveness towards such programs, particularly, using large-scale datasets (Bolton et al. 2000; Keh and Lee 2006; Kivetz and Simonson 2003). Thereby, we can offer robust insights into the directions and magnitudes of the effects under study. As 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. However, perhaps the railway industry differs in terms of customer demands being more predictable here than in other industries, or customers do not have much choices. However, customers could switch to a large number of other transportation providers to manage their way from A to B. Yet, it would be interesting to study these relationships in a highly competitive industry such as retailing.

**Managerial Implications**

First, as 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 program design in the two most important channels by highlighting linkages between consumer-inherent factors (like customer learning) and contingent factors (e.g. pricing contexts) in relation to channel choice. Identifying the linkages between (un)learning effects and cancelation behavior in Internet vis-à-vis counter purchase environments should help firms design more effective strategies for customer retention, which is obviously strongly linked to profitability. For example, given that both Internet usage and population age are on the increase, whereas Internet customers tend to be younger (Yoon 2002; Hitt and Frei 2002; Laroche et al. 2005; Miyazaki and Fernandez 2001; Weathers et al. 2007), the effects of learning in either channel on loyalty indicate a decreasing attractiveness of traditional channels, particularly if trying to retain customers in high-price offerings where decision-making is more likely ‘optimal’. This has implications for reorganizing and balancing the company mix of online versus offline information sources and purchase opportunities, particularly when introducing more expensive pricing schemes or additional quality services.

Second, 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 firm or opportunities to downgrade at regular intervals) in the long run, as the results suggest that often, customers reaching high decision quality in terms of optimality of usage are much more loyal to the firm, especially in high-price contexts. Consequently, optimizing communication efforts directed at consumers may be an effective means across channels to induce learning effects and thereby, increase customer loyalty. Based on the detailed documentation of linkages provide by our data, our results would help 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.

However, this study does not come without limitations. As one potential enhancement of the framework applied here, future studies may provide additional insights into the consumer perspective by modeling preferences towards alternative means of travel as they relate to contractual choices. Obviously, there might be important factors in addition to (un)learning, for example, such as unique product features or underlying consumer characteristics and motivations, e.g. household income, consumers’ environmental consciousness, susceptibility to social influence etc. Besides, our approach could be extended to include aspects related to market environment and competition among infrastructure providers, thereby assessing contractual choices against the background of economic and regional equity issues in a wider context. Further research could also focus on effects of the evolution of firms’ online and offline marketing practices and consumers’ choices (Brown and Dant 2011). An integrated analysis of such complex patterns of consumer 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.
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