DETERMINING THE IMPACT OF INTERNET CHANNEL USE ON A CUSTOMER'S LIFETIME

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In light of mature markets and increasing competitive pressure, retaining the existing customer base becomes crucial for the future success of a firm. As a consequence, firms are increasingly interested in understanding the factors influencing and driving customer retention. One factor that is hypothesized to have an impact on customer retention is the growing use of the Internet channel. Firms are interested in understanding whether and how the Internet use induces a change in customer retention.

The aim of this paper is to empirically quantify the impact of Internet use on customer retention when accounting for potentially present self-selection. Furthermore, the paper will derive managerial implications on how to use customer channel migration to improve overall customer retention. The results of the empirical study indicate a strong positive impact of Internet use on customer retention. Hence, migrating customers to the Internet channel has the potential to increase overall retention rates.

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INTRODUCTION

In light of mature markets and increasing competitive pressure, retaining and developing the existing customer base becomes crucial for the future success of a firm. Numerous benefits of customer retention are documented in the literature: Most importantly, retaining customers creates a stable pool of customers for a firm's products or services (Oliver, 1997). Furthermore, loyal customers buy more, are willing to pay higher prices, and generate positive word of mouth, thus suggesting a positive link between customer retention and profitability (Colgate & Danaher, 2000; Ganesh, Arnold, & Reynolds, 2000; Reichheld, 1993; Reichheld & Sasser, 1990; Zeithaml, Berry, & Parasuraman, 1996). Especially the cornerstone article on customer retention by Reichheld and Sasser (1990) which states that "reducing defections by 5% boosts profits by 25% to 85%" has emphasized this positive relationship. Despite recent research in noncontractual settings suggesting the link between customer retention and profitability to be weaker than expected (Reinartz & Kumar, 2000), firms are increasingly interested in understanding the factors influencing and driving customer retention (Rust, Lemon, & Zeithaml, 2004).

One factor which is hypothesized to have an impact on customer retention is the growing use of the Internet channel among customers (Reitsma et al., 2004; Schaaf, 2005). According to the U.S. Census Bureau, Internet retail sales for 2004 were $71 billion, or 25% higher than 2003 sales of $57 billion (U.S. Census Bureau, 2006). This rapid growth emphasizes the importance of the Internet as a distribution channel and calls for a thorough investigation of the relationship between Internet use and customer retention (Neslin et al., 2006; Shankar, Smith, & Rangaswamy, 2003).

The literature provides two explanations for potential differences in customer retention between Internet users and users of traditional channels and hence for a potential relationship between Internet use and customer retention: (1) a change in customer retention induced by the use of the Internet channel and (2) a self-selection of customers with above or below average loyalty levels to the Internet channel (Neslin et al., 2006; Verhoef & Donkers, 2005).

Regarding the first explanation, the current literature has generated several assumptions about how Internet use might lead to a change in customer retention (Neslin et al., 2006). Some of these assumptions suggest a negative relationship whereas others suggest a positive linkage. Shankar, Smith, and Rangaswamy (2003), for instance, assume that the competition on the Internet is only a few mouse clicks away. The opportunity to compare and contrast competing offerings with minimal costs causes an increase in competition based on price and hence a reduction in customer retention (Ansari, Mela, & Neslin, 2007; Kuttner, 1998; Sinha, 2000). Contrasting to this, the Internet is assumed as well to have a positive effect on customer retention (Wallace, Giese, & Johnson, 2004). Compared to the offline environment, the online environment offers more opportunities for personalized marketing as well as greater flexibility and convenience to the customer (Srinivasan, Anderson, & Ponnavolu, 2002; Wind & Rangaswamy, 2001). Furthermore, the Internet might create additional switching costs as customers learn how to use a new technology and hence improve their loyalty (Chen & Hitt, 2002; Reichheld & Schefter, 2000).

The second explanation for potential differences in customer retention between Internet users and users of traditional channels is reasoned by the so-called self-selection effect (Heckman, 1990). Customers are usually offered a free choice to select a channel through which to interact with the firm (Black et al., 2002). As a consequence, customers with certain characteristics might have an intrinsic preference for a specific channel. Several studies indicate that customers using the Internet are different from customers who buy from a traditional channel (Degeratu, Rangaswamy, & Wu, 2000). For example, Internet users are reported to be younger, better educated, and more affluent than the average population (Hitt & Frei, 2002; Verhoef & Donkers, 2005). At the same time, these customers are known to be less deal-prone and more loyal than other customers (Blattberg & Neslin, 1990). As a consequence, the systematic differences in customer characteristics between Internet users and users of traditional channels might have a direct impact on customer retention.

Even though both these theories provide an explanation for a potential difference in customer retention between Internet users and users of traditional channels, the managerial implications are quite distinct: the existence of an induced change in customer retention, for instance, can be exploited by multi-channel managers by designing customer channel migration strategies that aim to increase overall retention of the customer base (Ansari, Mela, & Neslin, 2007; Thomas & Sullivan, 2005). On the other hand, customer retention rates which are different across channels due to self-selection cannot be exploited by multi-channel managers. Migrating customers between the different channels would not affect retention rates (Gensler et al., 2006).

In summary, the initial research on the relationship between Internet use and customer retention points to three interesting questions: (1) How does Internet use affect customer retention? (2) Do customers with above or below average loyalty levels self-select to the Internet and hence bias the measurement of the induced change in customer retention? (3) What are the strategic implications of these findings for multichannel managers?

Accordingly, the aim of this paper is to empirically quantify the impact of Internet use on customer retention when accounting for potentially present self-selection. Furthermore, the paper will derive managerial implications on how to use customer channel migration to improve overall customer retention.

Previous research which tries to quantify the impact of Internet use on customer retention has produced mixed results (Neslin et al., 2006). This might be due to the fact that most previous work has neglected to account for the censored nature of active customer relationships when determining the average lifetime of Internet users and users of traditional channels. In addition, most previous work has not investigated the explanations for a potential difference in customer retention between Internet users and users of traditional channels and thus did not consider self-selection. Consequently, no managerial implications for customer channel migration have been derived.

This article is structured as follows. We first discuss the literature investigating the relationship between Internet use and customer retention and highlight its shortcomings. We then describe the data and methodology used for the empirical study conducted within this paper. Next, we present and discuss the results of the empirical study. We conclude by noting the managerial and research implications of the study's findings.

LITERATURE REVIEW

The literature review reveals five studies investigating the relationship between Internet use and customer retention (Hitt & Frei, 2002; Mols, 1998; Shankar, Smith, & Rangaswamy, 2003; Van den Poel & Lariviere, 2004; Verhoef & Donkers, 2005).

The first studies to investigate this issue are the articles by Mols (1998), Hitt and Frei (2002), and Verhoef and Donkers (2005). All these studies use data from the financial services industry and find a positive impact of using the Internet on customer retention. Mols (1998) employs a correlation analysis to investigate the relationship between the binary variable Internet use and the propensity to exit the financial institution. Hitt and Frei (2002) use the customer database of a financial institution to observe and compare the average length of relationship of Internet users versus users of traditional channels. Verhoef and Donkers (2005) use a probit model to estimate the effect of various channels on customer retention being measured as a binary variable.

However, all three studies do not account for the fact that a firm's customer base usually consists of a mix of active and completed relationships (Collett, 1994; Pfeifer & Bang, 2005; Reinartz & Kumar, 2000). Why this mix of active and completed customer relationships can cause problems in estimating the impact of Internet use on customer retention becomes especially apparent for the study by Hitt and Frei (2002). Calculating the average lifetime of a customer base requires determining the average lifetime of active and completed customer relationships. The calculation of an average lifetime for completed customer relationships is straightforward as the entire lifetime is by definition observable (Pfeifer & Bang, 2005). For the active relationships, on the other hand, only the length of relationship to date is observable but not the eventual lifetime. In these situations, we say that the customer lifetime is subject to right-censoring (Kalbfleisch & Prentice, 2002). A simple averaging of the length of relationship to date of the active customers with the complete lifetimes for the completed relationships is not appropriate as it will usually underestimate the mean lifetime (Pfeifer & Bang, 2005). Accounting for right-censoring is therefore a critical issue when modeling customer retention (Thomas, 2001).

The ratio of active relationships compared to completed relationships is generally higher for Internet users than for users of traditional channels. The results of Mols (1998), Hitt and Frei (2002), and Verhoef and Donkers (2005) underestimate the true impact of Internet use on customer retention.

This weakness is addressed by Van den Poel and Lariviere (2004) by applying a hazard model to account for right-censoring. Van den Poel and Lariviere (2004) use the data of a customer database provided by a large financial institution to estimate a hazard model which relates Internet use to customer retention. The results of their study indicate that the use of the Internet has no significant impact on a customer's retention.

Although the study by Van den Poel and Lariviere (2004) accounts for the issue of right-censoring, the study suffers from another weakness: it does not account for self-selection effects. The potential presence of self-selection effects and the lack of control for them might result in biased estimates of the effect of Internet use on customer retention. In order to determine an unbiased impact of Internet use on customer retention it is hence necessary to account for self-selection effects.

The literature review has identified only one study that considers and accounts for self-selection. The study by Shankar, Smith, and Rangaswamy (2003) uses the matching approach to eliminate potential self-selection effects.

The results of the study by Shankar, Smith, and Rangaswamy (2003) indicate a positive effect of the Internet use on customer retention after accounting for self-selection effects. Nevertheless, the study does not consider the issue of right-censoring. Hence, the results found in this study might again be misleading.

TABLE 1 Literature Review

ACCOUNT FOR SELF-SELECTION	ACCOUNT FOR RIGHT-CENSORING: NO	ACCOUNT FOR RIGHT-CENSORING: YES
No	– Mols (1998) – Hitt & Frei (2002) – Verhoef & Donkers (2005)	– Van den Poel & Lariviere (2004)
Yes	– Shankar, Smith & Rangaswamy (2003)	– THIS PAPER

As shown in Table 1, the studies investigating the relationship between Internet use and customer retention can be classified according to two dimensions: whether they account for right-censoring and whether they account for self-selection. Table 1 clearly shows that none of the studies investigates the impact of Internet use on customer retention and accounts at the same time for right-censoring and self-selection effects. This paper intends to close this gap in the literature in order to resolve the contradicting results in the literature and to determine the impact of Internet use on customer retention.

SAMPLE DESCRIPTION

We use data from a large European retail bank to determine the impact of Internet use on customer retention. Several factors underlie the decision to focus on financial services. First, Internet use has a long history in the financial services industry, suggesting a reasonable degree of familiarity and adoption of the Internet channel by banking customers (Hitt & Frei, 2002). Second, the potential to exploit the findings of the empirical study by developing customer channel migration strategies is especially large in the financial services industry. Banks fully control the multiple channels available to the customer. Hence, they do not depend on the goodwill of intermediaries to apply customer channel migration strategies.

The data covers a random sample of 10,000 customers of which 2,059 are active Internet users. We define a customer as an Internet user or online banking customer when he or she uses the bank's Internet channel during the observation period at least once per month in either

TABLE 2 Selected Customer Characteristics for Internet Users and Users of Traditional Channels

	INTERNET USERS (2059 OBSERVATIONS)	NON-INTERNET USERS (7941 OBSERVATIONS)	SIGNIFICANCE OF DIFFERENCE
Age (in years)	22.6	29.4	0.0000
Gender (% being male)	49.5 %	51.8 %	0.0667
Penetration of phone banking	7.1 %	0.3 %	0.0000
# of products per customer	1.3	1.4	0.0000
Penetration of security accounts	2.2 %	3.1 %	0.0378
# of transactions per customer	6.6	4.0	0.0000

the purchase or the after-sales stage of the purchase process (Balasubramanian, Raghunathan, & Mahajan, 2005; Neslin et al., 2006). The observation period covers in total 24 months from April 2002 until March 2004.

Over this 24-month period a large selection of variables has been collected for each customer. These variables can be grouped in three categories: socio-demographics, information about a customer's transaction behavior, and information about a customer's product portfolio. The socio-demographics include variables such as age and gender. The variables on a customer's transaction behavior detail the timing, the amount, and the channel used for every transaction executed in the observation period. Finally, the dataset provides information about all financial products owned by the customer and their usage.

All these variables are available only for the observation period. One exception to this is the variable "length of relationship." Not all customer relationships begin within the observation period. The majority of relationships have already started before being under observation. Hence, these customers were already at risk of leaving the bank before being observed. Had a customer churned earlier, we never would have encountered this customer in the dataset. This issue is called left-truncation and has to be accounted for when estimating the average lifetime of customers (Cleves, Gould, & Gutierrez, 2004).

The second issue that arises in the dataset is the issue of self-selection. Internet users in our sample are younger and have a higher likelihood to be female. Furthermore, Internet users have a higher likelihood to be phone banking customers, to own more products, and to do more transactions (see Table 2). As these variables may directly impact a customer's lifetime (Blattberg & Neslin, 1990), it is necessary to account for the issue of self-selection in this dataset (Cochran & Rubin, 1973).

The third issue which arises in the data is right-censoring. Out of the total 10,000 customers only 1,237 are being observed to churn within the observation period. We define a churned customer as someone who closed all her accounts. The remaining 8,763 customer relationships are not completed yet and are therefore right-censored.

A fourth issue that often arises in empirical studies is the existence of highly correlated explanatory variables. A difficulty to test for multicollinearity in this study is the time-varying nature of most of the explanatory variables. Since customers can have more than one value for a specific explanatory variable over time, one needs to find a dynamic way of dealing with correlations. We follow the procedure used in the paper by Mitra and Golder (2002) who also consider time-varying independent variables. In Table 3, we report the correlations among the variables later included in our model at the median time of observation across all observations. Multicollinearity does not appear to be a problem as no high correlations are present (Hair et al., 2005).

TABLE 3 Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age (1)	1.0000										
Gender (2)	0.0096	1.0000									
Length of relationship (3)	0.2817	0.0183	1.0000								
# of transactions (4)	−0.0937	0.0015	−0.0528	1.0000							
Interpurchase time (5)	0.0195	0.0037	0.0655	0.1272	1.0000						
Phone banking (6)	−0.0162	0.0182	0.0062	0.1037	−0.0042	1.0000					
# of products (7)	0.2016	−0.0093	0.5018	0.0441	−0.0179	0.0285	1.0000				
Joint account (8)	0.1564	−0.0076	−0.0530	0.0702	0.0115	0.0426	−0.0586	1.0000			
Securities account (9)	0.0179	0.0460	0.0937	−0.0044	0.0122	−0.0132	0.1595	−0.0240	1.0000		
Volatility (10)	−0.0289	0.0321	−0.0035	−0.0116	−0.0033	0.0011	−0.0067	−0.0105	−0.0047	1.0000	
Internet use (11)	−0.0771	−0.0064	−0.0482	0.3833	−0.0002	0.0527	0.0059	0.0468	0.0043	−0.0032	1.0000

To further test the existence of multicollinearity, we sequentially added variables to our model to assess the stability of the parameters and hence to ensure that multicollinearity has no harmful impact on the results. The analysis has shown that the parameter estimates for all covariates are highly stable. We can summarize that multicollinearity does not seem to have a meaningful impact on the results.

Finally, to avoid some customers having a disproportionately strong influence on the estimation results, we test for influential observations. We use the deviance residuals following the suggestions of Williams (1987), and Ortega, Cancho, and Bolfarine (2006) to identify thirteen observations which are potentially overly influential. Because an exclusion of these observations did not significantly change the parameter estimates of our hazard model, we decided to retain these observations in the estimation sample.

METHODOLOGY

As has been shown, it is important to account for self-selection, right-censoring, and left-truncation as ignoring them might lead to biased results. The following paragraphs will exhibit a two-stage process employing two distinct statistical methods to first account for self-selection and then for right-censoring and left-truncation. We describe the basic idea and the application of the two statistical methods.

Methodology to Account for Self-Selection Effects

The problem of self-selection is generally defined as a sampling problem. Customers are selected in the group of Internet users by means other than random sampling (Dehejia & Wahba, 1999). Instrumental variables (IV) methods and matching methods are the two most prominent approaches to disentangle treatment and selection effects (Wooldridge, 2002, p. 603). Both approaches are based on the idea that an individual may occupy two potential states (Roy, 1951; Rubin, 1974). At any time an individual is either in the treated (user of Internet channel) or untreated state (user of traditional channels) but cannot be in both states at the same time. A fundamental evaluation problem occurs, because the outcome (customer lifetime) is observable only in one state (Imbens, 2004).

(1) The instrumental variables (IV) method is a two-stage approach (Little, 1985). The first stage (outcome equation) describes the relationship between the outcome variable of interest as the dependent (e.g. customer lifetime) and the treatment variable (e.g. Internet use) and other variables as the independent

variables. In the second stage (selection equation) the treatment variable (e.g. Internet use) is a function of instruments (Amemiya, 1984; Heckman, 1974, 1976). Instruments have to be highly correlated with the treatment variable, but uncorrelated with the error term in the outcome equation, the other independent variables in the outcome equation, and the dependent variable (Dougherty, 2002; Wooldridge, 2003).

As noted by Maddala (1992, p. 462), because of these comprehensive requirements, it is rather hard finding valid instruments. This becomes even more difficult as it is not testable by definition whether all these requirements are met (Wooldridge, 2003, p. 463). The selection of suitable instruments can therefore only be based on economic theory and assumptions but cannot be based on statistical tests. As a consequence, the confidence in the estimation results rests only on the confidence in the assumptions that have been made to select the instruments. Yet the ability of the IV method to eliminate self-selection depends on the selection of appropriate instruments as inappropriate instruments lead to substantial biases in the estimated effects (Woglom, 2001).

Studies have shown that standard errors are inflated if the correlation between the chosen instrument and the treatment variable is small. Large samples are needed in order to find significant estimation results (Wooldridge, 2003, p. 468). It has been shown as well that in this case IV estimates are biased in the same direction as ordinary least squares (OLS) estimates. The magnitude of the bias of IV estimates approaches that of OLS estimates as the correlation between the instrument and the treatment variable approaches zero (Bound, Jaeger, & Baker, 1995).

On the other hand, simulations by Bound, Jaeger, and Baker (1995) have shown that even weak correlations between the instruments and the error term in the outcome equation can lead to large inconsistencies in the IV estimates.

A comparison of matching and the IV method by Blundell, Dearden, and Sianesi (2005) has demonstrated that matching leads to more accurate estimates than the instrumental variables method. We therefore believe that the matching method is the preferable method to determine the treatment effect for our study.[1]

(2) The matching approach intends to rebuild random sampling in a non-experimental context (Rosenbaum & Rubin, 1983, 1985). Its basic idea is to find in a large group of non-Internet users: those individuals who are similar to the Internet users with respect to specific covariates (Heckman, Ichimura, & Todd, 1998). Covariates are variables that simultaneously have an impact on a customer's lifetime and on a customer's decision to use the Internet channel (Sianesi, 2004; Smith & Todd, 2005). Ideally, the matched customers are identical to each other except for their use of the Internet (Rubin & Waterman, 2006). That being done, differences in customer lifetime between the group of Internet users and this well-selected group of users of traditional channels can be explained by Internet use.

The application of the matching method requires three steps: First, it is necessary to determine all covariates that simultaneously impact a customer's lifetime and channel use (Rosenbaum, 2002). The selection of the relevant covariates should be based on economic theory and previous research (Sianesi, 2004; Smith & Todd, 2005). After the relevant covariates have been identified, the similarity between individuals with respect to these covariates has to be determined. A common approach to determine this similarity is the so-called covariate matching (Zhao, 2004). Covariate matching uses a distance measure such as the Mahalanobis distance to calculate the similarity between two individuals in terms of covariate values (Imbens, 2004). The final step is to match customers based on their similarity. A straightforward approach is to match each Internet user to one user of traditional channels (one-to-one matching) (Cochran & Rubin, 1973). The search for matching individuals can be conducted either with or without replacement. "With replacement" signifies that users of traditional channels can be used in several occasions as matching

[1] As a comparison, we used as well the IV method to determine the treatment effect of using the Internet channel on a customer's lifetime. Unfortunately, the dataset offers only weak instruments. Nevertheless, the IV estimates produced comparable results (estimation results can be received on request from the authors). We take this as a further confirmation of our estimation results using the matching method.

partners. We use matching with replacement as it enhances the fit of the matched pairs and therefore eliminates self-selection bias more efficiently (Smith & Todd, 2005).

Methodology to Account for Right-Censoring

The issue of right-censoring arises when customers are still active at the end of an observation period. Thus, it is not observable whether a customer will churn one day or twenty years after the observation period ends (Pfeifer & Bang, 2005). One way to account for right-censored observations are hazard models (Cox & Oakes, 1996). The aim of hazard models is to relate the occurrence of events—for instance the churn of a customer—to a function of covariates (Hosmer & Lemeshow, 1999; Klein & Moeschberger, 2003). Covariates used in hazard models are defined as variables which are assumed to have an impact on a customer's lifetime (Kalbfleisch & Prentice, 2002). This estimated hazard model can be used to predict a customer's lifetime and thus account for right-censoring (Cox & Oakes, 1996).

The application of hazard models requires three steps. The first step is the identification of the covariates functioning as predictors of a customer's lifetime based on economic theory and previous research. The second step in modeling survival time requires choosing the parameterization of the survival function. Three types of hazard models can be distinguished: non-parametric, semi-parametric, and parametric models (Klein & Moeschberger, 2003). We opt for a parametric model as it is superior when intending to predict survival time (Cleves, Gould, & Gutierrez, 2004, p. 232) and more efficient in exploiting the available data compared to non-parametric and semi-parametric models (Cleves, Gould, & Gutierrez, 2004, p. 200). Non-parametric and semi-parametric models for instance ignore a customer's covariate values in time intervals when no churn occurs (Cleves, Gould, & Gutierrez, 2004, p. 200). Parametric models ignore no part of that information (Donkers, Verhoef, & De Jong, 2007; Singh, Hansen, & Blattberg, 2006). The third step in applying parametric hazard models is to choose a functional form for the baseline hazard. The choice of the distribution determines whether the hazard rate of the population under observation is increasing, decreasing, or constant over time. One particular distribution which is flexible enough to accommodate increasing, decreasing, and constant hazard rates is the Weibull distribution. We therefore opt for the Weibull distribution as it provides the necessary flexibility of the hazard model.

Methodology to Account for Left-Truncation

Left-truncation arises when customers come under observation only some known time after the onset of risk (Kalbfleisch & Prentice, 2002). Hence, these customers were already at risk of leaving the bank before being observed. Had a customer churned earlier, we never would have observed this customer. In other words, the observation of a left-truncated customer is conditioned on her not having churned before coming under observation. Not accounting for left-truncation will therefore underestimate the churn probability (Cleves, Gould, & Gutierrez, 2004, p. 35).

In parametric hazard models, left-truncation is easily dealt with. It requires a simple modification to the likelihood function (Cleves, Gould, & Gutierrez, 2004, p. 35). If a customer was at risk before coming under observation, then one more condition has to be added to the customer's contribution to the likelihood; namely, that she has not already churned until the onset of the observation period (Cleves, Gould, & Gutierrez, 2004, p. 35).

EMPIRICAL DESIGN

As indicated in the methodology section to account for self-selection, right-censoring, and left-truncation, it is necessary to apply a two-stage process using the matching method and a hazard model. The application of the matching method requires the identification of all covariates simultaneously influencing a customer's lifetime and Internet use (see Figure 1). Using a hazard model to estimate a customer's lifetime requires the identification of all relevant covariates having an impact on customer lifetime. This includes the variable of interest—in our case the use of the Internet channel—and additional variables to control for their effect on customer lifetime. In the following, we use economic theory and previous research to first identify the covariates simultaneously having an impact on customer lifetime and Internet use and

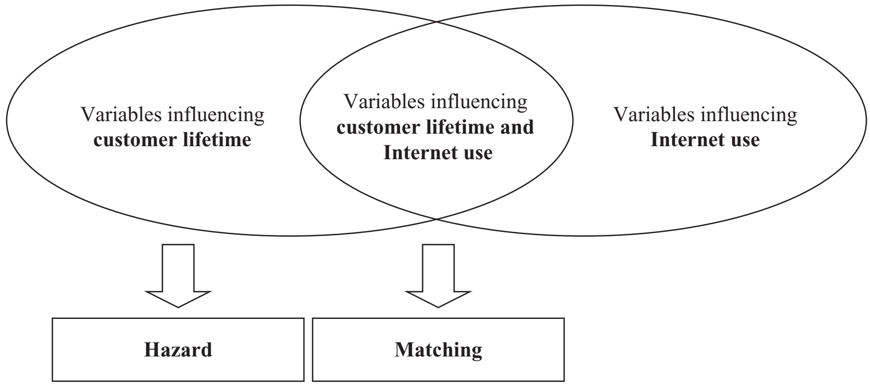

FIGURE 1

Relationship between Covariates for Matching and Hazard Models

afterwards additional covariates having only an impact on customer lifetime.

Variables Influencing Simultaneously Customer Lifetime and Internet Use

Several studies indicate socio-demographic variables as well as variables describing a customer's transaction and product usage behavior to impact customer lifetime and Internet use simultaneously. Among the socio-demographic variables, this includes age and gender.

Age. Mittal and Kamakura (2001) argue that older people have more stable preferences and thus show lower switching tendencies. At the same time, Inman, Shankar, and Ferraro (2004) find a significant impact of age on a customer's channel choice. Younger customers seem to have a preference for the Internet channel (Shankar, Smith, & Rangaswamy, 2003).

Gender. Dekimpe and Degraeve (1997) show that women have a higher churn probability. Simultaneously, studies identify an impact of gender on a customer's channel choice (Verhoef & Donkers, 2005).

Two variables describing a customer's transaction behavior simultaneously impact customer lifetime and Internet channel use: the number of transactions and phone banking use.

Number of transactions. An increase in the number of transactions is assumed to be negatively correlated with a customer's propensity to churn (Schmittlein, Morrison, & Colombo, 1987). The argumentation supporting an impact of the number of transactions on Internet use is based on the lower transaction costs incurred by customers on the Internet (Durkin et al., 2003). Customers conducting many transactions can over-proportionately benefit from these cost savings.

Phone banking. Phone banking provides customers with the possibility to conduct transactions independently from any bank opening hours (Black et al., 2002). This contributes to the convenience perceived by the customer and leads to higher retention (Durkin et al., 2003; Stone, Hobbs, & Khaleeli, 2002).

The phone and the Internet channel are both remote channels of interaction (Morrison & Roberts, 1998). Because of the similarity of channel characteristics, the likelihood of using the Internet should be higher for phone banking users (Montoya-Weiss, Voss, & Grewal, 2003).

Finally, we identify the variables describing a customer's product usage behavior which simultaneously impact customer lifetime and Internet use: the number of products and the ownership of a securities account.

Number of products. Previous research exhibits an impact of the total number of products used by a customer on customer retention (Huber, Lane, & Pofcher, 1998). At the same time, it is argued that the likelihood of Internet use increases with the number of products owned as the Internet channel enables customers to manage their products more efficiently (Hitt & Frei, 2002).

Ownership of a securities account. Some researchers investigate not only the impact of the number of products but as well the product-specific ownership on customer retention (Athanassopoulos, 2000; Levesque & McDouglas, 1996). Especially, the ownership of a securities account is hypothesized to impact customer lifetime. Similarly, the likelihood of adapting the Internet channel increases for customers owning a securities account (Hitt & Frei, 2002). The increased convenience of managing a securities account online attracts many customers to the Internet channel (Greywitt & Tews, 2001).

Additional Variables Influencing Customer Lifetime

After having identified the variables influencing simultaneously customer lifetime and Internet channel use, we now highlight additional variables which are hypothesized to have only an impact on customer lifetime and hence should be included in the hazard model. Although the focus of this study is to determine the impact of Internet use on customer retention, we also include additional variables in the hazard model in order to control for their effect. Not controlling for these additional variables would result in biased estimates for the impact of Internet use on customer retention.

The length of relationship and the interpurchase time are two additional variables describing a customer's transaction behavior which are hypothesized to influence customer lifetime.

Length of relationship. The literature indicates an impact of a customer's tenure with the firm on her churn behavior (Reichheld, 1996). One explanation might be that long-term customers develop a habitual purchase behavior (Waller, 1988). They have become accustomed to purchase the products and services of a specific firm.

Interpurchase time. A decrease in the interpurchase time might lead to a reduction in customer churn (Bhattacharya, 1998; Watson, Akselsen, & Pitt, 1998). Vilcassim and Jain (1991) found that with the passage of time between two purchases the likelihood of churn increases.

Variables describing a customer's product usage behavior which are hypothesized to be related to customer retention include ownership of a joint account and volatility of deposits.

Ownership of a joint account. Research shows that owners of a joint account have a lower likelihood to churn than the average customer (Eickbusch, 2002). One explanation assumes that joint accounts increase switching costs (Chen & Hitt, 2002).

Volatility of deposits. The volatility of deposits is defined as the cumulative percentage change across all deposits of a customer compared to the previous period. A large negative volatility indicates a sharp drop in a customer's assets deposited with the bank. One explanation of a sharp drop in a customer's assets might be that a customer is planning to close all accounts and is beginning to transfer all assets to a competitor (Bienenstock, Bonomo, & Hunter, 2004).

Table 4 summarizes the variables having a simultaneous impact on customer lifetime and Internet use and hence being used to account for self-selection, as well as the variables having only an impact on Internet use and hence being included in the hazard model.

FINDINGS

Several interesting findings emerge from the analysis. First, we will test the quality of our proposed approach to account for self-selection, right-censoring, and left-truncation. Second, we will determine the impact of the Internet use on a customer's lifetime when accounting for self-selection, right-censoring, and left-truncation. Third, we will provide further insights about the impact of selected covariates on a customer's lifetime. Finally, we will demonstrate that accounting for self-selection, right-censoring, and left-truncation significantly improves estimation results. Hence, it is important to account for them.

Quality of Matching Method to Account for Self-Selection Effects

The matching method is intended to eliminate systematic differences between the group of Internet users and the users of traditional channels and hence to account for self-selection effects. The quality of the

TABLE 4 Overview of Variables for Matching Method and Hazard Model

	INTERNET USE (STAGE 1 – MATCHING METHOD)		CUSTOMER LIFETIME (STAGE 2 – HAZARD MODEL)	
	RATIONALE	**SUPPORTING REFERENCES**	**RATIONALE**	**SUPPORTING REFERENCES**
Socio-Demographics				
Age	Internet is over-proportionately used by young customers	Inman et al (2004) Lee (2002)	Preferences become more stable which results in lower switching tendencies	Athanassopoulos (2000) Colgate & Danaher (2000)
Gender	Internet is over-proportionately used by male customers	Lee (2002) Verhoef & Donkers (2005)	Mixed findings in literature	Dekimpe & Degraeve (1997) Mittal & Kamakura (2001)
Transaction Behavior				
# of transactions	Customers with high level of transactions benefit from lower cost per transaction	Boehm & Gensler (2005)	Indicates customer's activity Active customers are less likely to churn	Schmittlein, Morrison, & Colombo (1987)
Phone banking	Phone banking customers are used to using remote channels	Montoya-Weiss, Voss, & Grewel (2003) Eastlick & Liu (1997)	Improved service offering and increased convenience	Van den Poel & Lariviere (2004)
Length of relationship	—		Time allows to develop trust and habitual behavior	Reichheld (1996) Ganesan (1994)
Interpurchase time	—		Indicates customer's activity Active customers are less likely to churn	Bhattacharya (1998) Watson, Akselsen, & Pitt (1998)
Customer Product Portfolio				
# of products	Eases management of accounts and increases convenience	Raijas & Tuunainen (2001)	More connections to bank increase switching costs	Huber, Lane, & Pofcher (1998) Van den Poel & Lariviere (2004)
Ownership of securities account	Eases management of accounts and increases convenience	Hitt & Frei (2002) Greywitt & Tews (2001)	More sophisticated connection to bank increases switching cost	Athanassopoulos (2000) Levesque & McDouglas (1996)
Ownership of joint account	—		More sophisticated connection to bank increases switching cost	Ganesan (1994) Jones, Mothersbaugh, & Beatty (2002)
Volatility	—		Might indicate preparations to close an account	Bienenstock, Bonomo, & Hunter (2004)

matching procedure can therefore be evaluated on whether systematic differences are still present after matching (Rosenbaum & Rubin, 1985; Smith & Todd, 2005). Table 5 presents a comparison between Internet users and the group of matched users of traditional channels. The comparison reveals a similar distribution for the relevant characteristics across both customer groups. Most differences in customer characteristics between both groups are insignificant after matching.

Another suitable indicator to assess the quality of the matching procedure is the standardized bias (SB) suggested by Rosenbaum and Rubin (1985). The standardized bias for all relevant characteristics is reduced significantly by the proposed matching procedure. Hence, the percentage reduction in bias suggests an acceptable quality level of the matching procedure. It can therefore be assumed that the self-selection bias with regards to the selected covariates is eliminated by the proposed matching procedure.

TABLE 5 Selected Variables for Internet Users and Matched Users of Traditional Channels

	INTERNET USERS (2059 OBSERVATIONS)	MATCHED NON-INTERNET USERS (1336 OBSERVATIONS)	SIGNIFICANCE OF DIFFERENCE
Age (in years)	22.6	22.5	0.1728
Gender (% being male)	49.5 %	51.4 %	0.2714
Penetration of phone banking	7.1 %	1.3 %	0.0000
# of products per customer	1.3	1.3	0.1376
Penetration of security accounts	2.2 %	2.3 %	0.8317
# of transactions per customer	6.6	6.1	0.0039

As a final test to evaluate the ability of the matching method to eliminate self-selection bias, we used the bounding approach proposed by Rosenbaum (2002). The basic question to be answered is whether the estimated treatment effect might be altered by omitted variables. In other words, we want to determine how strongly omitted variables must influence the selection process in order to undermine the implications of the matching analysis (Caliendo & Kopeinig, 2005).

Our analysis has shown that our proposed matching procedure is quite robust against omitted variables which affect assignment into treatment and the outcome variable simultaneously—the so-called hidden bias (DiPrete & Gangl, 2004). Hence, it is unlikely that omitted variables are challenging the conclusion about the estimated treatment effect.

Quality of Hazard Model to Account for Right-Censoring and Left-Truncation

Hazard models predict the expected lifetime for active customer relationships. The capability of the hazard model to account for right-censoring and left-truncation can therefore be evaluated based on the model's capability to accurately predict customer lifetimes. In order to evaluate the predictive validity of the model, we split the available data in an estimation and validation sample. The estimation sample covers the first 20 months and the validation sample the last four months of the 24-month observation period. We then use a predictive validity measure to evaluate the accuracy of the forecasts. A dimensionless predictive validity measure that relates the predicted to observed retention probabilities is the Mean Absolute Percentage Error (MAPE) (Armstrong, 1985). Studies have shown MAPE to be a reliable predictive validity measure (Armstrong & Fildes, 1995; Hyndman & Koehler, 2006).

The MAPE for the proposed two-stage process accounting for self-selection, right-censoring, and left-truncation is 29 percent, which represents a good forecast accuracy given a large number of values close to zero (Hyndman & Koehler, 2006).

After having evaluated the quality of the estimation results, the following section will now consider the estimation results of the proposed two-stage process.

Impact of Internet Use on a Customer's Lifetime

The estimation results of the hazard model presented in Table 6 indicate a positive impact of the Internet use on a customer's lifetime. According to Table 6, using the Internet reduces the likelihood of churn by 87.1 percent.

This dramatic decrease becomes apparent when comparing the survival function of Internet users with users of traditional channels. This comparison is depicted in Figure 2. The survival function of the Internet users lies considerably above the function of the users of traditional channels indicating a higher

TABLE 6 Estimation Results of Hazard Model

	HAZARD RATIO	Z	P > Z
Internet use	0.129	−5.59	0.000
Age	0.969	−1.83	0.067
Gender	1.202	1.88	0.060
Length of relationship	0.966	−2.56	0.011
# of transactions	1.004	0.57	0.567
Interpurchase time	0.993	−0.52	0.604
Phone banking	1.624	0.83	0.408
# of products	0.245	−13.12	0.000
Joint account	0.872	−0.59	0.554
Securities account	0.224	−2.41	0.016
Volatility	1.000	−7.84	0.000
P	1.739	12.05	0.000

probability of survival. For the Internet users, the probability of remaining a customer after five years is 96 percent, while the corresponding probability of an identical user of traditional channels is 74 percent. This comparison shows one more time the significant impact of using the Internet on customer retention. Negative effects of introducing the Internet seem outweighted in an industry such as financial services where trust is an important factor when selecting the provider of choice (Lee & Marlowe, 2003). Instead, customers using the Internet experience higher switching costs or an improved convenience which reduces the likelihood of churn.

The estimation results indicate that multi-channel managers interested in increasing the retention of their customer base can potentially use customer channel migration to reduce the churn rate among their customers. More precisely, they should migrate customers to the Internet channel or motivate newly acquired customers to use the Internet channel. Our results even indicate that migrating customers to the Internet channel might be more effective than using cross-selling activities in increasing customer retention (see Table 6).

The results of this empirical study provide a clear added value to multi-channel managers compared to the results of previous studies investigating the relationship between Internet use and customer retention. Rather than determining only the presence of an effect of Internet use on customer retention, the estimates of this empirical study quantify exactly the impact of Internet use on a customer's probability to remain with the firm. As a consequence, multi-channel managers can calculate by how many years a customer's lifetime is extended when being migrated to

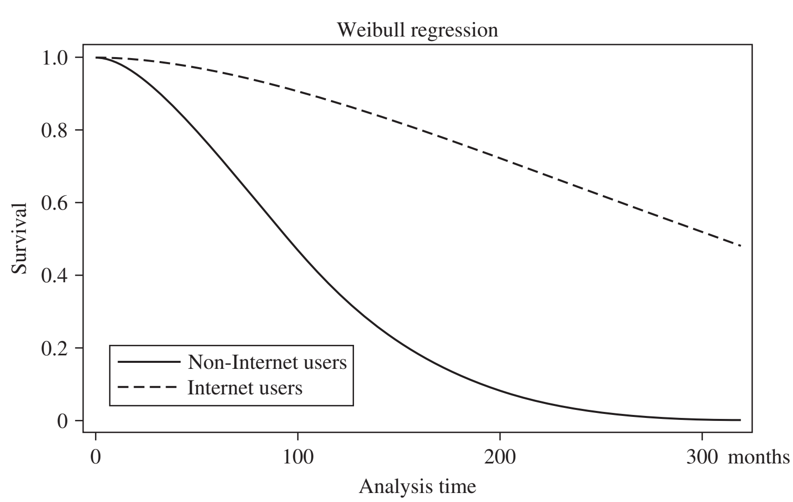

FIGURE 2

Comparison of Survival Function of Internet Users and Users of Traditional Channels.

the Internet channel. This offers the opportunity to evaluate whether the return on customer channel migration will be positive or negative.

Impact of Covariates on a Customer's Lifetime

Table 6 summarizes as well the estimated impact of selected covariates on a customer's lifetime.

In terms of socio-demographic variables we find that older customers are less likely to end the relationship with the bank. Every additional year of age decreases the likelihood of churn by 3.1 percent. This finding is in line with the results of the empirical study by Van den Poel and Lariviere (2004) and supports our assumed relationship. Similarly, we can confirm that men experience shorter lifetimes compared to women. Possible explanations can be found in the fact that women are more tolerant than men (Mittal & Kamakura, 2001) or that men may exhibit higher involvement towards financial products (Van den Poel & Lariviere, 2004).

Contrasting to the socio-demographic variables, the variables describing a customer's transaction behavior seem to have only a limited impact on a customer's lifetime. Except for length of relationship, all transaction behavior variables show no significant impact on customer lifetime including the number of transactions, the interpurchase time, and the phone banking use.

The length of relationship shows a positive impact on a customer's lifetime. Tenured customers, as expected, tend to have lower churn probabilities compared to customers who are with the firm only for a short period of time.

Regarding the number of transactions, it was argued that they reflect a customer's financial activity with the bank. Active customers are assumed to have a strong customer-firm relationship, but the estimation results show that the number of transactions has neither a positive nor a negative impact on customer lifetime. One explanation might be that customers leaving a bank as well have to display an increased level of activity. The insignificant impact of the interpurchase time can be reasoned by the long interpurchase times in the financial services industry. Customers in the financial services industry exhibit an average interpurchase time of more than four years (Kamakura et al., 2003). The limited observation period combined with such a long interpurchase time could provide an explanation for the insignificant effect. The insignificant effect of phone banking use on customer retention might be due to the fact that phone banking has become a commodity service. The majority of banks offers this service and cannot use it as a factor of differentiation.

Our results reveal a significant impact for the majority of variables describing a customer's product usage behavior. The number of products used by the customer dramatically reduces the likelihood to churn. Each additional product reduces the churn probability by more than 75 percent. This relationship confirms the relevance of cross-selling activities in the financial services industry (McKelvey, 2004). Cross-selling seems not only to increase revenues generated with the customer but also to prolong customer relationships (Van den Poel & Lariviere, 2004). Especially securities accounts seem to be an adequate product for cross-selling with the aim to increase a customer's lifetime. Our results suggest that the ownership of a securities account improves the likelihood of retaining a customer by 87.6 percent. Finally, the volatility of deposits has a significant but negligible positive effect on customer churn. An increase in volatility reduces the churn probability by less than 1 percent. Contrasting to this, the ownership of a joint account, which was hypothesized to positively impact a customer's lifetime, does not exhibit a significant effect.

Table 6 not only contains the estimated hazard ratios of the hazard model, but also its ancillary shape parameter. The shape parameter that is estimated by the data indicates whether the population experiences constant, increasing, or decreasing hazard rates as time passes. The estimated shape parameter indicates increasing hazard rates for the population. In other words, the likelihood of an instantaneous customer churn increases as time passes. This significant estimation result supports as well our choice of the Weibull distribution as a parameterization of the baseline hazard.

Impact of Self-Selection and Right-Censoring

The literature review has described five studies investigating the relationship between Internet use and customer retention of which none accounts simultaneously for the issue of self-selection and right-censoring. On theoretical grounds, it has already been argued that this might lead either to an over- or underestimation of the true effect of Internet use on customer retention.

In order to prove empirically the importance to account for the issue of self-selection and right-censoring, we compare the impact of the Internet use on a customer's lifetime according to the two dimensions used as well to categorize the existing literature (see Table 7): whether self-selection has been accounted for and whether right-censoring has been accounted for. Hence, a total of four results for the impact of Internet use on customer retention can be contrasted and the effect of accounting for self-selection and right-censoring can be determined.

Table 7 summarizes the estimation results and presents the average customer lifetime for Internet users and users of traditional channels. Comparing the average lifetime of these two groups allows inferring the impact of Internet channel use on a customer's lifetime and hence customer retention.

In three of the four cases, users of traditional channels appear to have longer lifetimes compared with Internet users. Only when accounting for self-selection and right-censoring simultaneously, this picture is reversed.

Quadrant 1: Not accounting for self-selection, not accounting for right-censoring. The average length of relationship for Internet users and users of traditional channels is 16 and 43 months respectively. In other words, users of traditional channels have been with the bank 27 months longer than Internet users. As a consequence, users of traditional channels appear to have 2.69 times longer lifetimes than Internet users. Following this simple mean comparison, it would be logical to conclude that the Internet significantly decreases a customer's lifetime and hence multi-channel managers should intend to reduce the use of the Internet channel.

Quadrant 2: Not accounting for self-selection, accounting for right-censoring. The basic message that users of traditional channels have longer lifetimes than Internet users is not changed when accounting for the censored nature of customer relationships. Nevertheless, the estimated average lifetime for both groups increases significantly compared to the observed length of relationship. For instance, the lifetime for Internet users increases from 16 to 99 months and for users of traditional channels from 43 to 189 months. This sharp increase is due to the large percentage of customer relationships in the dataset which are still incomplete. The hazard model accounts for this right-censoring and estimates the eventual lifetime of a customer based on her observed

TABLE 7 Impact of Self-Selection and Right-Censoring

ACCOUNT FOR SELF-SELECTION		ACCOUNT FOR RIGHT-CENSORING: NO	ACCOUNT FOR RIGHT-CENSORING: YES
No	Lifetime of non-Internet users	43 months	189 months
	Lifetime of Internet users	16 months	99 months
	Lifetime ratio (non- / Internet users)	2.69	1.91
	MAPE	60%	39%
Yes	Lifetime of non-Internet users	28 months	84 months
	Lifetime of Internet users	16 months	99 months
	Lifetime ratio (non- / Internet users)	1.75	0.85
	MAPE	41%	29%

covariates. Even though the basic message that Internet use seems to increase a customer's lifetime is not changing, it is worthwhile noting that the average lifetime of users of traditional channels is now only 1.91 times longer than for Internet users. Hence, the relative difference in lifetimes between Internet and traditional channel users has been decreasing as the hazard model compensates for some of the difference in the observed length of relationship.

Quadrant 3: Accounting for self-selection, not accounting for right-censoring. As we account for self-selection, we see the average length of relationship for users of traditional channels drop from 43 to 28 months. This is due to the matching method which corrects for non-random sampling based on the selected covariates and implicitly corrects as well for the fact that long-time customers tend to use traditional channels. The average length of relationship of customers using the traditional channels after accounting for self-selection amounts therefore to only 28 months which is 1.75 times longer than the average of 16 months for Internet users. These results suggest that the length of relationship decreases when using the Internet channel by twelve months (28 − 16 = 12). The self-selection effect towards the Internet appears to be negative as well and amounts to 25 months (43 − 28 = 25). In other words, when simply comparing the observed average length of relationship and not accounting for self-selection, the negative effect of the Internet would be overstated by 25 months.

Quadrant 4: Accounting for self-selection, accounting for right-censoring. The average customer lifetime of Internet users and users of traditional channels is 99 and 84 months respectively when accounting for self-selection and right-censoring simultaneously. The ratio between the lifetime of traditional channel users and Internet channel users drops for the first time below one to 0.85. This means that users of traditional channels have a lifetime which is only 85 percent of the lifetime of Internet users. This result is in line with our findings from the hazard model which found a positive effect of Internet use on a customer's lifetime.

The directional change when accounting for self-selection and right-censoring not only indicates a positive impact of Internet use on a customer's lifetime but also indicates a strong negative self-selection effect towards the Internet. It seems that customers with shorter lifetimes and hence less loyalty tend to prefer the Internet to the traditional channels.

Table 7 clearly shows that accounting for self-selection and right-censoring is essential. Not only does it influence the effect size, it also influences the direction of the estimated effect.

To judge whether these results are meaningful, it is necessary to verify the validity of these estimation results. This can be achieved by testing whether the predictive validity improves when accounting for self-selection and right-censoring.

As can be seen from Table 7 the MAPE improves significantly when accounting for right-censoring. In the case of not accounting for self-selection (upper quadrants) the MAPE is reduced from 60 to 39 percent when accounting for right-censoring. In the case of accounting for self-selection (lower quadrants), the MAPE even drops from 41 to 29 percent when accounting for right-censoring. These results indicate that the predictive validity improves significantly when accounting for right-censoring.

The MAPE further indicates that the predictive validity of the model improves also when accounting for self-selection. The MAPE drops from 60 to 41 percent in case of not accounting for right-censoring and from 39 to 29 percent in case of accounting for right-censoring.

In summary, we can state that accounting for self-selection and right-censoring offers the highest predictive validity with the lowest MAPE of only 29 percent.

CONCLUSION

Customer retention generates numerous benefits and hence is a critical aim of many firms. A small shift in customer retention can already make a large difference for the profitability of the firm. As a consequence, firms are increasingly interested in understanding the factors driving customer retention. One factor which is hypothesized to have an impact on customer retention is the growing use of the Internet channel. Firms are interested in understanding whether and how the Internet use induces a change in customer retention.

The aim of this paper was to empirically quantify the impact of Internet use on customer retention when accounting for potentially present self-selection effects. Furthermore, the paper derived managerial implications on how to use customer channel migration to improve overall customer retention.

A literature review identified five studies investigating the relationship between Internet use and customer retention. Nevertheless, all five studies provide different results and hence do not offer a clear indication about the effect of Internet use on a customer's lifetime. This might be due to methodological weaknesses. They either do not account for the issue of self-selection or the issue of right-censoring. Not accounting for self-selection or right-censoring tends to over- or underestimate the true impact of Internet use on customer retention.

We therefore proposed a two-stage process using two statistical methods to account for the issue of self-selection and the issue of right-censoring. In the first stage, we employed the matching method to eliminate potentially present self-selection. In the second stage, we estimated a hazard model on the matched sample in order to estimate a customer's lifetime and hence to account for right-censoring.

The results of the empirical study indicate a strong positive impact of Internet use on customer retention. The use of the Internet channel has been shown to reduce the risk of churn by nearly 88 percent. Customers using the Internet channel therefore exhibit a significantly longer average lifetime.

The results of the empirical study identify customer channel migration as a potential measure to increase the retention of a firm's customer base. Multi-channel managers interested in reaping the benefits of increased customer retention might want to raise the use of the Internet channel among customers. This will allow to significantly prolong the average customer lifetime with the firm. The estimates of the hazard model even suggest that migrating customers to the Internet channel might have a larger effect on customer retention than cross-selling activities aiming to sell one additional product. This finding emphasizes the relevance of customer channel migration for the future success of a firm.

The empirical study showed furthermore that accounting for self-selection and right-censoring is essential in order to identify the true impact of Internet use on a customer's lifetime. More specifically, not accounting for self-selection and right-censoring not only over- or underestimates the true effect but might even be misleading about the direction of effects. Multi-channel managers being interested in the impact of Internet use on a customer's lifetime will have to account for self-selection and right-censoring as they might otherwise draw misleading conclusions for their channel management strategies.

While we believe this study has increased our understanding about the impact of Internet use on a customer's lifetime, the work is subject to limitations that provide avenues for future research.

First, the study is subject to potential sample selection issues. Geographically, we only study German consumers. Furthermore, we only have access to the data of one specific bank. It might be that the behavior of this bank's customers is very much distinct to the general population.

Second, we only have data for a two-year time frame. In order to estimate the customer lifetime and hence the impact of Internet use on customer lifetime with higher confidence, a longer timeframe would be desirable. Because of the short observation period, the estimated impact of Internet use on a customer's lifetime might not be constant over time. It might even be that the estimated impact will vanish in the future as customers get used to the use of the Internet.

Third, the matching method uses the so-called conditional independence assumption (CIA) in order to identify the treatment effect. The CIA assumes that, given a set of observed covariates, potential outcomes (e.g. customer lifetime) are independent of treatment assignment (e.g. Internet use) (Heckman et al., 1998). This implies that selection is solely based on observed characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed by the researcher. In other words, the matching method does not control for variables not being observed (Ho et al., 2007). Clearly, this is a strong assumption but it is the central methodological concern of many scholarly articles

(Ho et al., 2007). We tried to strengthen the confidence in the matching method by testing how strongly an unobserved variable must influence the selection process in order to undermine the implications of the matching analysis. Our analysis has shown that our proposed matching procedure is quite robust against the presence of unobserved variables.

In summary, we contribute to the literature by (1) empirically determining the impact of Internet use on customer retention, (2) by deriving managerial implications for customer channel migration strategies, (3) by accounting for self-selection and right-censoring in the data, and finally (4) by applying a combination of the matching method and hazard models to a marketing problem.

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