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An Empirical Investigation of Customer Retention: Addressing Unique Challenges in Customer-Firm Relationships

Angeliki Christodoulopoulou

AN EMPIRICAL INVESTIGATION OF CUSTOMER RETENTION: ADDRESSING UNIQUE CHALLENGES IN CUSTOMER-FIRM RELATIONSHIPS

BY

ANGELIKI CHRISTODOULOPOULOU

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ACCEPTANCE

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Richard Phillips, Dean

DISSERTATION COMMITTEE
Dr. V. Kumar (Chair)
Dr. Alok Saboo
Dr. Koray Cosguner
Dr. Agata Leszkiewicz

ABSTRACT

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ANGELIKI CHRISTODOULOPOULOU

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Committee Chair: Dr. V. Kumar

Major Academic Unit: Marketing

Effective customer retention is vital to the survival and prosperity of any customer-centric organization. Systematic examination of different aspects of the customer's relationship with the firm has the potential to provide valuable insights to support retention efforts. However, the nature of the purchasing options and relationship patterns inherent in each industry require managers to shift their focus on varied aspects of the relationship, thus posing unique challenges. One such challenge is examined in the first essay of this dissertation, in a setting where customer-firm relationships are intermittent, with customers being lost to and won back again by the firm. A unifying model for joint estimation of the customers' second lifetime duration, multiple repeat churn reasons, and heterogeneity in exhibiting a related churn reason is developed to study this relationship. The findings support the existence of a cured group of returning customers, defined as those who are not susceptible to churn due to a repeated reason. Another challenge is examined in the second essay, which involves a setting where the structure of the purchasing options is a combination of contractual and noncontractual services. The complexities and dynamics of the customer-firm relationship and customers' underlying commitment to it are modeled through a hidden Markov model, incorporating the dependency between the two purchase processes. The findings suggest that contractual and noncontractual purchase behaviors are distinct but interrelated.

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CHAPTER 1 – INTRODUCTION

Retaining customers is vital for any organization in any industry. Whether the products offered are at the introduction, growth, or maturity stages of their lifecycle, retaining profitable customers is key to the firm's survival and prosperity. Systematic examination of different aspects of the customer's relationship with the firm[1], or the customer-firm relationship, has the potential to provide valuable insights to support retention efforts. However, it is not always clear which aspects managers should focus on; following established methods can sometimes fail to provide an accurate description this relationship. Thus, what is the best approach in investigating the customer-firm relationship? The answer depends on the nature of the purchasing options and relationship patterns inherent in each industry. For example, the prevalent purchasing options structure may be contractual, noncontractual, or a combination of the two. Furthermore, the pattern of the customer-firm relationships may be continuous or intermittent. Depending on the case, unique challenges may arise. This dissertation investigates and offers the methods to understand and manage two such challenges in two empirical contexts.

The first challenge pertains to a setting where customer-firm relationships are intermittent, with customers being lost to and won back again by the firm. In such cases, firms develop win-back strategies to rectify issues that cause customer churn and rebuild the relationship with lost customers. To better support retention, it is important to understand how the revived relationship evolves and possibly ends again. The first essay – Chapter 2 – studies customers' second lifetime and their repeat churn behavior in the context of the mature service

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[1] The terms organization, company, and firm are used interchangeably in the remainder of this study.

industry of telecommunications. A Mixture Cure Competing Risks model, jointly estimating the second lifetime duration, multiple churn reasons, and customers' heterogeneity in exhibiting a related churn reason is developed to examine this relationship. The proposed model is estimated using information on customer behavior and marketing activities during customers' first and second lifetimes. The results support the existence of a cured group of returning customers, defined as those who are not susceptible to churn due to a repeated reason. The findings suggest that mitigating repeat churn behavior can extend customers' second lifetime tenure and increase profitability over customers' lifetime.

The second challenge involves a setting where the structure of the purchasing options is a combination of contractual and noncontractual services. Specifically, the customer-firm relationship and customer lifetime value are examined in the context of the health and fitness industry. Despite the increasing importance placed on fitness nowadays, health and fitness clubs are still faced with problems in customer retention, like any other business. The second essay – Chapter 3 – aims to improve customer retention in this industry, where customers may engage in two types of distinct purchase behaviors. Specifically, each customer may make contractual purchases (memberships), noncontractual purchases (standalone access), or both, while the intensity and sequence of these purchases may follow any pattern. Prior research on purely contractual and purely noncontractual relationships is extensive, but it does not address situations where both purchase elements may occur, simultaneously or sequentially. The complexities and dynamics of this customer-firm relationship are examined through an underlying commitment lens, manifested through customers' contractual and noncontractual purchases. The varying stages of relationship commitment are modeled through a hidden Markov model, incorporating the dependency between the two purchase processes. This model is estimated using information on customer transactions over a three-year period. The results support the existence of two stages in the customer-firm relationship, each one with unique purchase patterns. The findings suggest that the two purchase behaviors are distinct but interrelated.

CHAPTER 2 – ESSAY 1:

AN INVESTIGATION OF CUSTOMERS' REPEAT CHURN BEHAVIOR

INTRODUCTION

Recent developments in customer relationship management (CRM) examine the *extended customer lifecycle*, exploring what happens when customers suspend a service. In the wireless industry, carriers such as T-Mobile and Verizon offer a reimbursement of up to $650 per line to cover early termination fees to customers who are willing to make a switch from another service provider (T-Mobile 2017; Verizon 2017). In the gas and energy industry, market deregulation has increased competition, giving the customer the power to choose the best provider with the help of dedicated websites such as Power2Switch.com. As a result of decreasing monetary switching costs, contractual service industries face a unique problem: customers tend to churn repeatedly. However, firms have begun to recognize that lost customers may not be "dead opportunities" (Griffin and Lowenstein 2001) and extend attractive promotional offers to win them back. After successful reacquisition, firms need to understand this renewed relationship to fortify customer retention strategies and contain the looming risk of churn.

Rebuilding the relationship with lost customers is the main objective of win-back management (Stauss and Friege 1999). The re-initiated customer-firm relationship, or a customer's *second lifetime* (SLT), is typically marked by the signing of a new contract. As such, we distinguish it from the customer's *first lifetime* (FLT) – the relationship with initially acquired prospects. The SLT is different from the FLT for both the customer and the firm. Reacquired customers' experience with the firm clearly distinguishes them from newly-acquired customers (Stauss and Friege 1999). They have knowledge and expectations about the firm's offerings and procedures gained in their FLT and through win-back interactions. From the firm's perspective, the revived customer relationship is distinct from the relationship with new customers because the firm has information about the reacquired customers' preferences from their past and present interactions (Griffin and Lowenstein 2001; Stauss and Friege 1999). Considering the FLT and SLT customer behavior and characteristics, the firm can offer them targeted and personalized services. Therefore, the clear distinction between the pre- and post-churn phases of the customer-firm relationship requires that SLT strategies are investigated in addition to FLT strategies.

The win-back literature has focused on several aspects of the SLT such as customer reacquisition, SLT duration and profitability (Kumar, Bhagwat, and Zhang 2015; Thomas, Blattberg, and Fox 2004). Prior research has identified the main reasons why customers quit services (Keaveney 1995), showing that knowledge of the problem areas can help the firm proactively address FLT churn (Stauss and Friege 1999; Tokman, Davis, and Lemon 2007). However, the repeat churn behavior of returning customers has not yet been investigated. Henceforth, we use the term *repeat churn behavior, SLT churn behavior,* or *reason for SLT churn*, to refer to the termination of customers' SLT and the reasons behind it. Although the reason for FLT churn is indicative of SLT duration (Kumar, Bhagwat, and Zhang 2015), questions remain if it is a significant predictor of the reason behind SLT churn. We believe additional research is needed to gain more insights into the SLT churn behavior.

Based on FLT reasons for churn, firms can identify areas for improvement and effectively engage in win-back dialogue with lost customers. If firms succeed in addressing the underlying cause for dissatisfaction, customers will not churn for the same reason in the future. We refer to such customers as *cured customers*. Cured customers are satisfied with the firm's win-back efforts to improve the problem areas underlying their FLT churn. However, this does not apply to every returning customer; there will be a share of *uncured customers* who are more likely to return to the firm only because of the incentives included in the firm's reacquisition activities. These customers may churn again for any reason, including the one that caused their FLT churn, despite the firm's reacquisition efforts. Therefore, we propose that the two types of returning customers, *cured* and *uncured*, are susceptible to different churn reasons in the future. Both types of customers are still at risk of defection in the SLT, whether for the same or other reasons, so predicting SLT churn remains a crucial aspect of managing reacquired customers.

Firms need to know *when* and *why* a returning customer will churn again, and *how* this propensity to repeat churn changes over time. For example, do price-sensitive customers churn earlier or later than quality-demanding customers? Further, given the firm's efforts to rectify problem areas underlying the first churn, is a returning customer still at risk of churning for the same reason again in the SLT, or is the damaged relationship with this customer cured, so that if they churn it will be for other reasons? If the latter is true, will a cured customer exhibit longer tenure compared to an uncured customer? Finally, CMOs want to know if a customer's SLT behavior is indicative of the propensity to repeat churn, understand how current marketing interventions influence SLT tenure, and how to design effective retention strategies.

This study attempts to provide answers to the above issues by developing a model of customers' repeat churn behavior using transactional data that document such behavior in a contractual industry. The rich dataset at our disposal includes FLT and SLT records of customer behavior – subscription details and referral activities, and the firm's marketing actions – communications to customers, as well as FLT and SLT churn behavior. This is the first study using both FLT and SLT information on customer behavior and the firm's marketing activities. We model the SLT churn through a survival analysis approach, which is well-suited to include a) a churn probability that can change over time, b) right-censoring, and c) time-varying covariates.

Since the focus of the study lies on SLT retention, the analysis is conditional on customers being reacquired. To uncover the two groups of returning customers (cured and uncured), we draw upon the literature on mixture cure (MC) survival models. To allow for the SLT to terminate due to one of multiple competing events (i.e., causes for churn), we use the competing risks (CR) survival framework. The unifying framework is the *mixture cure competing risks model* (MCCR), which accounts for 1) the possible existence of a cured and an uncured customer group, where the former will not repeat the FLT churn reason (MC), and 2) multiple reasons to churn in both groups (CR). Basu and Tiwari (2010) first proposed an MCCR model describing different patterns of time dependence in the survival of cancer patients. This framework is extended by (a) allowing the customer to belong to one of two groups with a probability, (b) incorporating time dependence, and (c) including time-varying covariates for the prediction of SLT churn. This study contributes to the marketing literature in the following ways:

1. It predicts the time and the reason for customers' SLT churn and shows that it is different from FLT churn.
2. It employs SLT information on customer service and behavior characteristics and marketing actions to predict customers' repeat churn behavior and thus help managers design retention strategies in real time.
3. It distinguishes between two groups of returning customers, cured and uncured, where the former does not repeat the FLT churn reason.
4. It uses FLT information on customer service and behavior characteristics and marketing actions to recognize cured customers and thus help managers leverage this knowledge in the renewed relationship.

5. It proposes a unifying MCCR model which jointly accounts for the cured and uncured groups of customers and multiple reasons to repeat churn, while incorporating covariates to predict cure probabilities and SLT duration.

The rest of this chapter is organized as follows: First, we review the relevant customer SLT literature explaining the marketplace need, the research gap, and the contributions of this study in each research area in more detail. Then, we discuss the empirical setting of our study, including the data set and the modeling framework. Subsequently, we introduce the relevant methodological literature and derive the MCCR model. Finally, we present the results and a discussion of our findings, their implications, limitations, and future research opportunities.

SLT LITERATURE REVIEW

Extant literature on customers' SLT has primarily focused on reacquisition, with select studies investigating SLT duration and profitability. Reacquisition is the first aspect of SLT management, aiming to identify and target lost customers who are worth reacquiring, and design win-back activities to bring them back and start their SLT. Stauss and Friege (1999) discuss the steps that firms should undertake to implement a win-back strategy based on customer value and reason for churn, in order to yield a higher return on reacquisition investment. Building on this framework, Griffin and Lowenstein (2001) provide advice on designing successful customer reacquisition strategies and practices. Reinartz, Krafft, and Hoyer (2004) show a positive association of the existence of systematic reacquisition processes with the strength of the organization.

Several factors influence a lapsed customer's decision to renew the contract. Win-back activities need to offer attractive incentives to convince the customer to renew the relationship, and may include an individually-adapted monetary compensation (a rebate, a coupon, a price discount, etc.), or service upgrade (Stauss and Friege 1999). Consistent with economic theory, larger monetary and non-monetary incentives increase the perceived value of the win-back offer and the reacquisition probability (Thomas, Blattberg, and Fox 2004; Tokman, Davis, and Lemon 2007). Adapting the win-back offer to address the reasons for customer defection has been recommended to improve reacquisition (Stauss and Friege 1999) and also empirically supported (Kumar, Bhagwat, and Zhang 2015; Tokman, Davis, and Lemon 2007). Furthermore, a customer's reacquisition probability is affected by their satisfaction from the interactions and outcomes of the revival process (Homburg, Hoyer, and Stock 2007); customer characteristics (Kumar, Bhagwat, and Zhang 2015; Thomas, Blattberg, and Fox 2004), including variety seeking and involvement (Homburg, Hoyer, and Stock 2007); as well as past experience, such as the FLT tenure, service experience, marketing communication, and the defection behavior (Kumar, Bhagwat, and Zhang 2015).

Research on aspects beyond customer reacquisition is scarce, despite the importance of SLT duration and profitability for customer retention. Strategies based on retention models developed for the FLT (e.g., Reinartz and Kumar 2003) are not directly applicable to the SLT, since the two lifetimes are conceptually different due to the knowledge and experience the reacquired customer has about the firm, and vice versa. Notable exceptions are the studies by Thomas, Blattberg, and Fox (2004), who examined the influence of the FLT duration, the defection duration (i.e., time elapsed since churn), and the offered price on SLT duration using a survival model assuming constant churn rates; and by Kumar, Bhagwat, and Zhang (2015), who investigated the impact of FLT experience and behavior on SLT duration using a Tobit type linear duration model.

Table 1: Select Empirical Studies Modeling Customer Defection and/or Reacquisition in Contractual Settings

	SLT DV	SLT (FLT) Multiple defection reasons	SLT IVs	Win-back	Time-varying CB	Modelling approach	Industry	Contributions/benefits
Thomas, Blattberg, and Fox (2004)	Y	N (N)	Y	Y	N	Split hazard model	Newspaper	Develop optimal pricing for reacquisition and SLT to maximize SLT value
Homburg, Hoyer, and Stock (2007)	N	N (N)	N	Y	N	SEM, logit	Telecommunication services	Find drivers of customers' revival-specific satisfaction and probability of reacquisition
Braun and Schweidel (2011)	N	N (Y)	N	N	N	Hierarchical competing risks model	Telecommunication services	Predict FLT duration and probability to churn due to different reasons based on geo-demographic data
Kumar, Bhagwat, and Zhang (2015)	Y	N (Y[1])	N	Y[1]	N	Censored Tobit model with probit selection	Telecommunication services	Predict the relation between SLT profitability and customer information: FLT customer behavior, reason for defection, and win-back offer
THIS STUDY	Y	Y (Y)	Y	Y	Y	Mixture cure competing risk model	Telecommunication services	Estimate jointly the SLT duration and the probability to repeat churn due to multiple defection reasons, accounting for a fraction of cured customers

[1] As an explanatory variable.

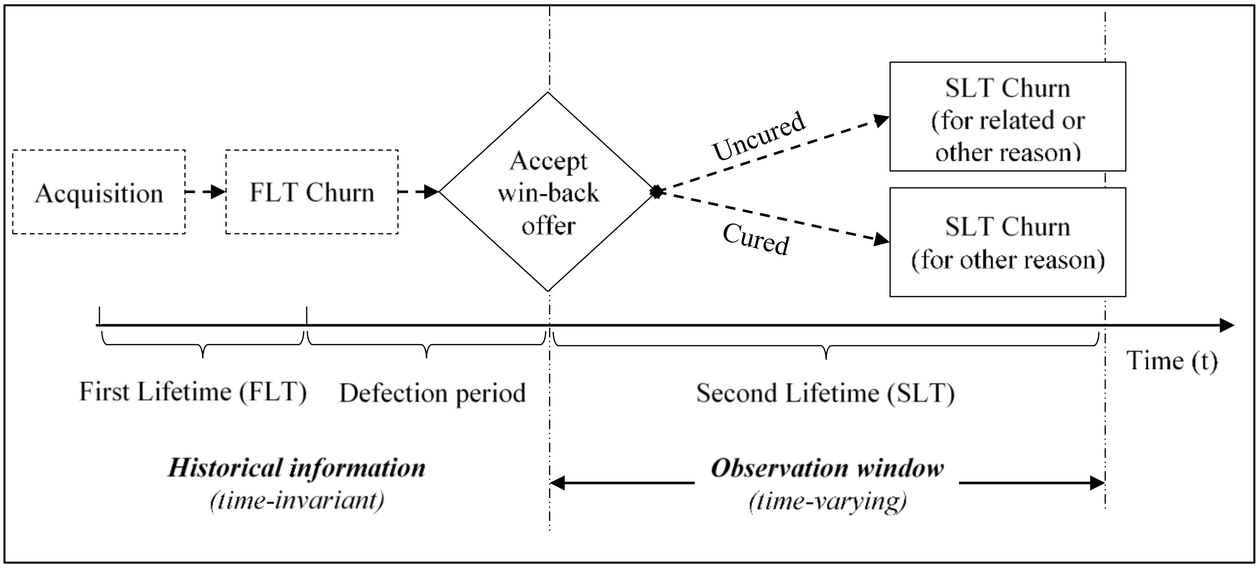
Understanding why customers quit the service is a key element of CRM. Keaveney (1995) identified various reasons for customer defection. Among these reasons, some are beyond the firm's control, but the most frequent critical incidents are price and service issues (service failures, failed service encounters, and response to service failure). Customers' motives to churn are an important factor for segmentation and targeting of lapsed and reacquired customers (Stauss and Friege 1999), because customers who repeatedly switch between providers tend to have short SLTs. Bogomolova (2010) found that the customers who switch *to* the competition will have more positive brand evaluations and higher propensity to consider the brand in the future than customers who switch *from* the brand due to its negative qualities. In an empirical study, Kumar, Bhagwat, and Zhang (2015) show that a customer's motive for defection is a good predictor of their reacquisition likelihood, SLT duration, and SLT profitability. Specifically, customers churning for price reasons have higher probability of reacquisition than customers churning for service-related reasons, but their SLT is shorter, and their monthly profitability is lower.

Studying churn behavior of reacquired customers should be part of a holistic SLT management approach, as repeat churn has become a significant concern for firms in various industries but has been overlooked by the extant SLT literature. Table 1 shows how this study compares to relevant prior research studies modeling customer defection and/or reacquisition in contractual settings. The studies of Kumar, Bhagwat, and Zhang (2015) and Braun and Schweidel (2011) appear to be the closest benchmarks, but neither predicts repeat churn behavior, which is the first objective of this study. Specifically, Kumar, Bhagwat, and Zhang (2015) focus on the duration of the SLT but overlook the reasons for SLT defection. Braun and Schweidel (2011) model both the time and reason for FLT churn, which we show is different from SLT churn. This study also investigates whether customers' SLT churn patterns are different from their FLT churn reasons, which is not the case in any prior research. Further, it examines the effects of SLT customer behavior and marketing actions on SLT churn behavior, which is a significant development for SLT retention strategies over the research by Kumar, Bhagwat, and Zhang (2015), whose findings are based on historical FLT data. Accounting for time-varying SLT covariates is also a contribution over the Braun and Schweidel (2011) study, where only time-invariant geodemographic characteristics are included. Finally, we uncover the two groups of returning customers and examine the effects of win-back offers and FLT information on the likelihood of customers' being in the cured group. This is the first attempt to comprehensively and empirically study SLT churn behavior, in terms of both the SLT duration and the reasons behind relationship termination.

EMPIRICAL SETTING

The data used in this study comes from a U.S.-based telecommunications provider, comprising of individual-level data on a random sample of 10,000 customers, reacquired in January 2012, and tracked throughout their SLT until December 2015. We randomly assigned 7,054 customers to the calibration sample, and the remainder 2,946 customers constitutes the holdout sample used for model validation. The available information includes data collected from each customer during the observation period: the time and reason of churn, customer activities, and marketing actions by the firm. Historical information on each customer is also available: customer activities and marketing actions in the FLT, the time and reason to churn, a record of the lapse duration, and the type of win-back offer they received. Figure 1 illustrates the timeline of the customer-firm relationship for customers in the sample.

Figure 1: The Customer Relationship Timeline



Customers' FLT began with the initial acquisition and ended upon the original contract termination[2]. The firm obtained information about the reason for their defection through a representative-administered survey and classified them as related to *price* and/or *service*[3]. In December 2011, the firm conducted a one-time reacquisition campaign and mailed out attractive win-back offers to all customers who had ended their FLT in the previous two to six months. Only first-time churners were contacted. To address the most common reasons for customer churn, the firm designed the win-back offers based on a price discount, a service upgrade, or a combination of a price discount and a service upgrade. All offers were similar in value: the price

[2] In this industry, customers may change conditions to their contracts before expiration by, for example, purchasing additional services and bundling them or changing the rate plan, which may involve signing new contracts for add-on services. We attribute a customer's FLT and/or SLT as the customer-firm business relationship, which stops when the customer suspends all services.

[3] There is a small fraction of customers (less than 2%) who defected due to reasons that do not fall under the any of the above-mentioned categories (classified by the firm as *other reasons*). This category represents factors that are outside of the firm's control and, therefore, the firm did not target such customers with win-back offers.

Table 2: Operationalization of Variables

Variable	Abbreviation[1]	Operationalization
SLT[2] Variables (Varying by Month)		
SLT Revenue	SLT_revenue	The monthly revenue generated by the customer in dollars
SLT Cross-buy	SLT_xbuy	The number of different service categories the customer is subscribed to
SLT Referrals	SLT_refer	The number of customer referrals brought to the firm by the customer
SLT Complaints	SLT_comp	The number of complaints made by the customer
SLT Recoveries	SLT_reco	The number of service recoveries the firm completed for the customer
SLT Phone calls	SLT_call	The number of phone calls made by the firm to the customer
SLT Emails	SLT_email	The number of emails sent by the firm to the customer
SLT Direct mails	SLT_dmail	The number of direct mails sent by the firm to the customer
SLT Promotion	SLT_win_ promo	An indicator of whether the promotion offered in the win-back is active (1=active, 0=inactive)
FLT[3] and Demographic Variables (Time-Invariant)		
FLT Churn		Categorical variable indicating: 1 – a price related reason, 2 – service related reason, 3 – price and service related reason.
FLT Defection period	taway	The number of days from the time the customer defected until he or she was reacquired by the firm (i.e., the period between the FLT and SLT)
FLT Tenure	FLT_tenure	The number of days the customer retained service with the firm prior to the first defection (i.e., the duration of the FLT)
FLT Revenue	FLT_revenue	The average monthly revenue generated by the customer during the FLT in dollars
FLT Cross-buy	FLT_xbuy	The total number of different service categories the customer was subscribed to during the FLT
FLT Referrals	FLT_refer	The average number of yearly referrals by the customer in the FLT
FLT Complaints	FLT_comp	The average number of yearly complaints made by the customer in the FLT
FLT Recoveries	FLT_reco	The average number of yearly service recoveries the firm completed for the customer in the FLT
FLT Phone calls	FLT_call	The average number of yearly phone calls made by the firm to the customer in the FLT
FLT Emails	FLT_email	The average number of yearly emails sent by the firm to the customer in the FLT
FLT Direct mails	FLT_dmail	The average number of yearly direct mails sent by the firm to the customer in the FLT
Gender	gender	An indicator of the customer's gender (1=male, 0=female)
Age	age	The customer's age in years
Income	income	The customer's household income in dollars
Household size	hhold	The number of people in the customer's household
Education	educ	The customer' highest attained education level in years
Dependent Variables		
SLT Duration		The number of days the customer retained service with the firm after reacquisition divided into non-overlapping monthly intervals
SLT Churn		Categorical variable indicating: 0 – no churn, 1 – a price related reason, 2 – service related reason, 3 – price and service related reason.

[1] Abbreviated variable names are used in Equations.
[2] SLT = Second Lifetime
[3] FLT = First Lifetime

discount included in the bundled offer was lower than the one in the standalone price win-back, and so was the service upgrade benefit. These offers were randomly assigned to the lapsed customers and expired after 30 days. The promotional benefits were in effect only for the first six months of the customer's renewed contract, which was typically signed for a period of twenty-four months but could be suspended without penalty after the promotional period expired. After twenty-four months, the contract was automatically renewed until the customer suspended the service or chose a new contract. As such, the SLT began with re-signing a customer after the initial churn period, and either ended with cancellation of all their services (for the second time) or lasted beyond the observation window. Each churning customer was asked to participate again in a standard exit interview administered over the phone.

During the FLT and SLT the firm kept records of each customer's behavior and marketing contacts. The FLT data contains historical information measured in yearly averages over the FLT or at the end of the FLT (it is aggregate and time-invariant). Customers' service characteristics include the average monthly FLT revenue from their service purchases and the number of services included in the contract throughout the FLT. More aspects of customer experience are captured through their successful referrals of new customers to the firm and their complaints. Firm actions include service recovery records[4] as well as customer retention efforts in the form of marketing communications through phone calls, emails, and direct mail (measured

[4] In this setting, complaints and recoveries are only partially related. Examples of service recoveries include restoring service after outage or offering free service (or discounts) for a short period of time. The firm can restore service even without a customer notification (e.g., if an entire area is affected). On the other hand, not all complaints are considered by the firm. Thus, there is not always a direct link between a customer filing a complaint and the firm considering it or not. The correlation between complaints and recoveries in our sample is 0.13 in the SLT and 0.11 in the FLT (both are significant).

Table 3: Descriptive Statistics

SLT Variables	**Mean**	**Std. Dev.**
SLT Revenue (per month in dollars)	97.62	25.8
SLT Cross-buy	1.730	.47
SLT Referrals (per month)	.079	.11
SLT Complaints (per month)	.014	.14
SLT Recoveries (per month)	.005	.08
SLT Phone calls (per month)	.076	.03
SLT Emails (per month)	.510	.41
SLT Direct mails (per month)	.320	.45
SLT Promotion (per month)	.156	.36
FLT and Demographic Variables	**Mean**	**Std. Dev.**
FLT Defection period (in days)	108.7	19.8
FLT Tenure (in days)	1427.3	109.2
FLT Revenue (per month in dollars)	85.80	15.3
FLT Cross-buy	1.560	.47
FLT Referrals (per year)	.090	.04
FLT Complaints (per year)	.100	.04
FLT Recoveries (per year)	.067	.03
FLT Phone calls (per year)	.780	.33
FLT Emails (per year)	3.960	.64
FLT Direct mails (per year)	2.510	.42
Gender (% male)	57.4%	.47
Age	39.90	9.56
Income (in dollars)	98,116.40	23,691.40
Household size	2.910	1.25
Education (in years)	16.01	2.18
Dependent Variables	**Mean**	**Std. Dev.**
SLT Duration (in days)	1352.4	110.7
N=7,054 customers		

in yearly averages). Each customer's defection period is the time elapsed (in days) between the termination of their first contract and the start of a new one.

The data collected during the observation window includes the same information on customer behavior, but it pertains to the SLT and is observed monthly, including: the revenue from customer's SLT service purchases, the level of their cross-buy across different services, their successful referrals of new customers to the firm, and their complaints. Firm actions like service recovery efforts, are also recorded on a monthly basis. Marketing communications are captured by the monthly number of phone calls made, emails sent, and direct mails sent to each customer. Information on the duration of the promotion embedded in the win-back offer is also available, captured by an indicator variable taking a value of 1 for the months when the offer is in effect (i.e., the customer pays a discounted price and/or receives a free service upgrade), and 0 otherwise. We note demographic information about the customer's gender, age, income, household size, and education as the measures of observed heterogeneity at our disposal. Table 2 summarizes the available data and details the variable operationalization. The descriptive statistics are presented in Table 3.

Since the study's main objective is to investigate repeat churn behavior, we first examine the relationship between customers' FLT and SLT defection reasons, presented in Table 4. There are two distinct churn motives ("price" and "service"), but three churn categories ("price", "service", and "price-and-service"). We see that 2,320 (2,106) customers ended their FLT (SLT) because of price, 2,430 (2,124) ended because of service issues, and 2,304 (2,082) suspended the contract reporting both issues as the reason for defecting, which is distinguished here as a separate churn category. About ten percent of the reacquired customers maintained service until the end of the observation period, thus censoring does not pose a threat. Although the marginal distributions of FLT and SLT churn appear evenly distributed among defection categories, their joint distribution reveals that customers generally do not report the exact same churn category twice. This is true in only about 32 percent of the cases. Therefore, information on past churn reasons is not sufficient to predict future churn behavior, consistent with research suggesting that the FLT can be different from the SLT (Stauss and Friege 1999).

Table 4: Customers' Churn Reason in the FLT vs. SLT

	SLT Churn Reason				
FLT Churn Reason	No churn	Price	Service	Price & Service	*Total*
Price	248*	683	712*	677	2320
Service	265*	740*	692	733	2430
Price & Service	229*	683	720	672	2304
Total	742	2106	2124	2082	7054

* Latent cure status

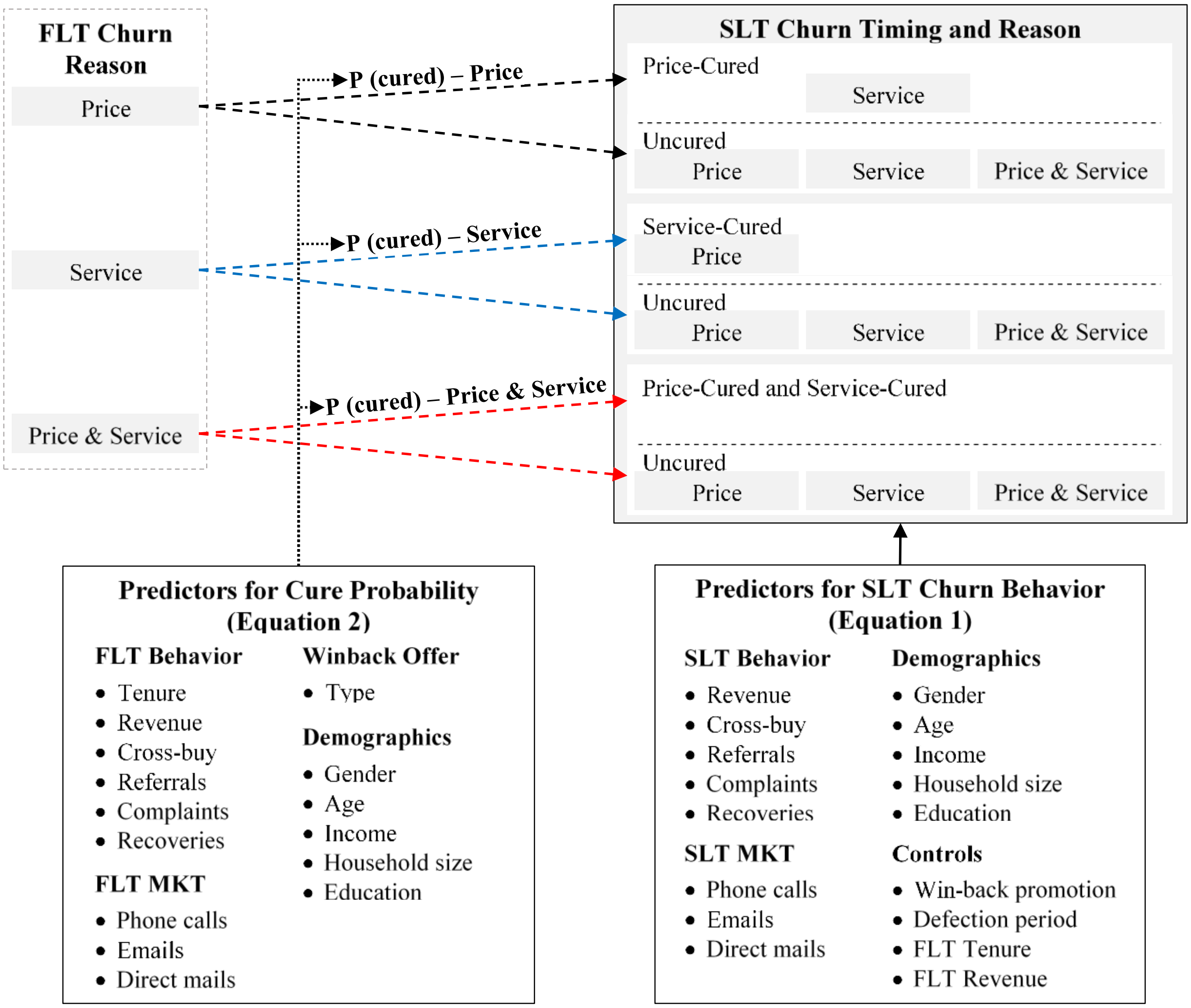
Modeling Framework

The customer-firm relationship is conceptually analogous to a patient-doctor relationship. Based on the patient's history and symptoms, the doctor gives a diagnosis and determines the course of treatment. If the treatment is successful, the patient will recover from the illness, but will eventually die for other reasons. If the treatment is unsuccessful, the patient may succumb to the illness or die of any other disease (whichever comes first). Similarly, customers' FLT churn reasons are symptomatic of the dissatisfaction areas, so the firm will try to amend them. If this "treatment" is successful, the customer will become cured and not succumb to this type of churn. Otherwise, the customer will stay dissatisfied with that aspect of the service. Regardless of the cure status, the customer is still vulnerable to churn in the SLT because of other reasons. Thus, as the doctor keeps his patients under observation following treatment, the firm should monitor the customers' behavior for signs of possible SLT defection. With this in mind, we build a model of repeat churn behavior whose overview is presented in Figure 2.

Repeat churn behavior. To explain repeat churn behavior, we jointly predict the SLT tenure and defection motive (dependent variable), leveraging the individual-level information on SLT customer characteristics and firm activities (covariates). We expect customer behavior associated with positive (vs. negative) experience to be indicative of longer (vs. shorter) SLT tenures, and assume a homogenous effect of covariates on the type of churn (Kumar, Bhagwat, and Zhang 2015). Specifically, SLT revenue should be positively related to SLT duration, consistent with literature on customer retention (Reinartz and Kumar 2003). Therefore, high revenue customers will have lower churn propensity. Cross-buying behavior and relationship duration are positively associated in the FLT (Reinartz and Kumar 2003), but an inverse U-shape association has been documented between FLT cross-buy and SLT duration (Kumar, Bhagwat, and Zhang 2015). Accordingly, we expect customers with moderate levels of cross-buy to be the least likely to churn, as implied by the inverse U-shape relation between contemporary (SLT) cross-buy and SLT duration. Customer referrals indicate satisfaction with the firm (Biyalogorsky, Gerstner, and Libai 2001), which in turn is leads to longer relationship duration (Bolton 1998). Therefore, we expect referrals to be associated with longer SLT tenures and lower SLT churn propensity. Complaints express customer dissatisfaction with the service or the firm, so they should be negatively related to SLT duration, while recovery efforts should have a positive effect. We generally expect more complaints (vs. service recoveries) to indicate a higher (vs. lower) propensity of suspending service.

Marketing communications should have positive and synergistic effects on SLT duration, consistent with the evidence obtained from different contact modes (Kumar, Bhagwat, and Zhang 2015; Reinartz, Thomas, and Kumar 2005). Thus, we expect marketing communications to be negatively associated with a customer's SLT churn. Furthermore, observed heterogeneity is captured through the available demographic characteristics. Our expectations for their association with customers' SLT churn are guided by findings of Kumar, Bhagwat, and Zhang (2015) in a similar setting. Most of the demographic variables are expected to indicate longer SLT tenures, and accordingly, have a negative association with churn timing.

Figure 2: Conceptualizing the Modeling Framework



Finally, we control for certain FLT, defection, and win-back aspects. Specifically, we control for the months when the win-back promotion is in effect. During this period, customers enjoyed attractive win-back benefits and faced a penalty for contract cancelation – a strong incentive to maintain contract. Therefore, this promotion should be negatively related to SLT churn timing. Regarding the defection period, prior research (Kumar, Bhagwat, and Zhang 2015) has found it has a nonlinear effect on the likelihood of reacquisition, but not on the SLT duration. We cautiously expect the length of the defection period to be negatively related to the SLT churn propensity, but also test for the existence of a diminishing effect. Finally, we control for the length of the customer's FLT and the average monthly revenue generated by the customer during the FLT. These controls indicate satisfaction with the firm, leading to a positive association with relationship duration (Bolton 1998), so we expect a negative relationship with SLT churn.

***Cured vs. uncured customers*.** We distinguish between two types of returning customers, characterized by unique patterns of first and second churn behavior. They emerge as a result of the firm's efforts to improve on dissatisfaction areas causing customers to end their FLTs. These efforts are implemented through various tools during the post-churn dialogue (win-back offers in this context). If the firm rectifies the issues underlying their FLT churn, some returning customers will be cured. Since there are two distinct churn reasons, the returning customers can be "price-cured" and/or "service-cured". Consequently, customers who ended their FLT because of price (service), if cured, will defect due to the remaining non-price (non-service) reason in the SLT, i.e., service (price). Customers who ended their FLT due to both reasons (price and service), if cured, will become price-cured and service-cured, and will not succumb to any type of SLT churn. In contrast, uncured customers will be susceptible to all churn categories in their SLTs, regardless of the FLT churn reason. The shaded box in Figure 2 illustrates this idea in this empirical setting.

Customers' latent cure status (binary dependent variable) can be predicted by incorporating the information available to managers at the time of reacquisition. Specifically, the cure probability predictors include the FLT customer service and behavior characteristics in terms of tenure, monthly revenue, cross-buying, referral activity, and complaining. We also include the effects of FLT firm actions regarding service recoveries and marketing communications through phone calls, emails, and direct mailings. Our general expectations are parallel to the discussion on SLT duration. The more positive the FLT relationship is, the easier it is for the firm to successfully address the dissatisfaction area, increasing the probability that a customer will be cured. The effects of observed heterogeneity on the cure probability are captured through the demographic variables. Lastly, win-back offers with incentives that correspond to the FLT reason have greater potential to improve the relationship with the customer than ones without such incentives, increasing the cure chances.

MIXTURE CURE COMPETING RISKS MODEL

A joint model of the time and reason for SLT churn in which cured and uncured customers are susceptible to different types of churn is developed. The proposed model is based on a survival analysis framework, previously adopted in various CRM applications (Braun and Schweidel 2011; Kumar, Zhang, and Luo 2014). Seetharaman and Chintagunta (2003) give an excellent review different survival models with an application to purchase timing decisions. To predict when SLT churn will happen and what type of event it will be, we apply the competing risks (CR) method (Kalbfleisch and Prentice 2002). This methodology has been used in marketing to model purchase timing and brand choices (Seetharaman and Chintagunta 2003) and customers' FLT churn behavior (Braun and Schweidel 2011). There are a couple of limitations of the CR approach relevant to this study. First, it assumes that the competing risks are mutually exclusive, while here one of the churn reasons is a combination of the others ("price-and-service" reason)[5]. In the proposed model setup, it is treated as a separate competing risk, and we

[5] When event types are not mutually exclusive, similar competing risks are usually aggregated into a single risk category. However, this it is not advisable here, as the "price-and-service" reason cannot be clearly classified into "price" or "service" category.

interpret the results accordingly. Second, the CR method assumes that all individuals are exposed to the same risks.

The development of mixture-cure (MC) models is mainly attributed to the progress in cancer research (Berkson and Gage 1952; Farewell 1982). As a result of the treatment (or the cure), a fraction of long-term survivors emerges in the population of patients, $0<p<1$, affecting the subsequent duration through the survival function $S(t) = p + (1\text{-}p)S_0(t)$, which does not tend to 0 but has a probability limit $\lim_{t \to \infty} S(t) = p$. This is a property unique to the cure model, implying that only some individuals will ever experience an event. The cure model is a mixture model, as the survival function captures the unobserved heterogeneity of failure times in the cured and uncured subpopulations, with $S_1 = 1$ being the survival function of the cured group. The model has various applications in marketing: Sinha and Chandrashekaran (1992) modeled banks' adoption of ATMs, allowing some banks to be non-adopters; Srinivasan, Lilien, and Rangaswamy (2006) studied the emergence of a dominant design in a new product category. However, MC models do not allow for multiple types of events, which prevents us from understanding the time dependence in several reasons for SLT churn. Furthermore, MC applications are limited by the assumption that an individual is cured of one risk only.

A few studies have brought the MC and CR approaches under a unified framework. Larson and Dinse (1985) developed a mixture competing risks model where the probability for the type of failure was modeled as a logistic regression, and the conditional time-to-event followed a piecewise exponential model. Basu and Tiwari (2010) developed a Bayesian model for cancer survival with competing causes of death, where the patient population is a mixture of cured and uncured individuals, and the primary risk is removed for the cured patients. Therefore, it allows for different risk sets in the cured and uncured group.

We incorporate the unified MC and CR frameworks to a unique marketing application, where the reasons for SLT churn are the competing risks and win-back offers act as cures. Our approach offers several modeling contributions. First, we propose a novel way to address a problem of overlapping competing risks. Second, we allow for the cures to target more than one risk. Furthermore, our MCCR model is discrete-time and incorporates monthly SLT information in the hazard rates. We also use FLT information to parametrize the cure probability. We develop the model in several steps. First, we introduce the competing risks to account for multiple causes for churn. The cure effect is next incorporated as the MCCR model. To maintain notational compactness, the time-varying covariates for the SLT duration and the predictors of cure probability are included later, followed by a discussion of endogeneity concerns.

Model Setup

Assume a sample of N reacquired customers, and let $\mathcal{S} = \{1, \cdots, s\}$ be a set of s mutually exclusive churn reasons, so $\mathcal{S} = \{\text{price, service}\}$ in this setting. At the end of the FLT (SLT) the individual may report any combination of reasons in $\mathcal{S}$ that caused them to suspend the contract. Thus, there are $k=2^s-1$ ways the customer's FLT (SLT) can end, forming the risk set $\mathcal{P}^+(\mathcal{S}) = \{\mathcal{C}\colon \mathcal{C} \subseteq \mathcal{S} \text{ and } \mathcal{C} \neq \emptyset\}$. This is the power set of $\mathcal{S}$, excluding the empty set, and in this setting $\mathcal{P}^+(\mathcal{S}) = \{\{\text{price}\}, \{\text{service}\}, \{\text{price, service}\}\}$. For the ith individual the observed data is

$$(t_i, C_{it}, x_{it}, x_i^{FLT}, C_i^{FLT}) \text{ with } t = 1, \ldots, t_i$$

where t_i is the observed SLT duration in days. This can be divided into intervals with grouping points $[t_0,t_1),[t_1,t_2),\cdots,[t_{a-1},t_a),[t_{ai},t_\infty)$, where $t_0 = 0$, $t_{ai}=t_i$ is the observed SLT duration. The intervals are not required to be of the same length. C_{it} is a vector taking values $C_{it}=j$ ($\mathcal{C}_j \in \mathcal{P}^+(\mathcal{S})$, $j=1,\ldots,k$) if churn is observed in period t and 0 otherwise. We also use $C_i = \Sigma_t C_{it}$ to denote censored ($C_i=0$) and uncensored cases ($C_i>0$). The vector of covariates x_{it} are the variables predicting the SLT duration observed in month *t*, and x_i^{FLT} comprises of variables affecting the cure probability. Finally, $C_i^{FLT} = l$ ($\mathcal{C}_l \in \mathcal{P}^+(\mathcal{S})$, $l=1,\ldots,k$) represents all reason(s) why the customer churned in the FLT[6]. Without loss of generality, we assume that the churn probability and the covariates are constant within the time interval. The observed outcome is the pair (t_i, C_{it}).

Modeling Multiple Causes to Churn with the Competing Risks Framework

An active customer is at risk of churning due to any of the competing risks in $\mathcal{P}^+(\mathcal{S})$, and the time to churn is a random process specific to each risk. Once a customer churns due to one type of churn, others are no longer possible, so we only observe the duration $t = \min t_j$, $j=1,\ldots,k$. Conditional on having a contract just before *t*, the probability that the customer churns in time *t* due to risk *j* is the cause-specific hazard is $h_j(t|\alpha_j,\gamma_j) = \alpha_j\gamma_j t^{\gamma_j - 1}$, and is assumed to follow a Weibull distribution with α-scale parameter and γ-shape parameter ($\alpha,\gamma > 0$). The Weibull specification allows for both proportional and accelerated effect of the covariates on the survival, and was adopted previously in related literature (e.g., Braun and Schweidel 2011; Kumar, Zhang, and Luo 2014). The effect of all forces causing the customer to churn is captured through the sum of the integrated cause-specific hazards $H(t|\ \theta_1, \ldots, \theta_k) = \sum_{j=1}^{k} \alpha_j\, t^{\gamma_j}$, $\theta_j = [\alpha_j, \gamma_j]$. Another relevant quantity is the survival function, defined as a probability that the customer maintains the service until period *t*, which in the CR context implies that none of the k events occur before *t*. Under risk independence the survival function is $S(t) = \prod_j S_j(t_j) = \exp(-H(t))$, and it is the likelihood contribution of a customer *i* who does not churn within the observation window. If

[6] We require that the churn causes are coded in the same way for the FLT and SLT. For example, in this application $\mathcal{C}_1$={price}, $\mathcal{C}_2$={service}, and $\mathcal{C}_3$={{price},{service}}are coded as C_{it}=1,2,3, respectively.

customer churn is observed, $C_i = j$, then their likelihood contribution is the hazard rate corresponding to risk *j* times the survival function. Combining right-censored and complete durations[7], the likelihood function is:

$$L_i(t_i, C_i) = h(t_i, C_i = j)^{\delta_{ij}} \exp\left(-\sum_{r=1}^{k} \alpha_r t_i^{\gamma_r}\right) \tag{M1}$$

where $\delta_{ij} = I[C_i = j]$.

Defining the Mixture of Cured and Uncured Customers

Consider a customer who ended their FLT due to one of the churn reasons in $\mathcal{S}$, or any possible combination thereof, indicated by $C_i^{FLT} = l$ ($\mathcal{C}_l \in \mathcal{P}^{+}(\mathcal{S})$). If cured, this individual will not repeat any churn reason(s), and SLT and FLT churn reasons will not have common elements, i.e. $\mathcal{C}_j \cap \mathcal{C}_l = \emptyset$. Subscripts (j,l) represent the reason for the second and first churn. Formally, a cured customer is susceptible to risks from a reduced set $\mathcal{P}^{-l}(\mathcal{S}) = \{\mathcal{A}: \mathcal{A} \subseteq \mathcal{S} \text{ and } \mathcal{A} \cap \mathcal{C}_l = \emptyset\}$, and in this application $\mathcal{P}^{-1}(\mathcal{S}) = \{\text{service}\}$, $\mathcal{P}^{-2}(\mathcal{S}) = \{\text{price}\}$, $\mathcal{P}^{-3}(\mathcal{S}) = \emptyset$. It follows that if $\mathcal{C}_j \cap \mathcal{C}_l \neq \emptyset$ we know that the customer is uncured (Case 1). When the customer churns because of risk in $\mathcal{P}^{-l}(\mathcal{S})$ (Case 2) or maintains contract beyond the observation window (Case 3), the cure status is unobserved. We identify these customers with an asterisk in Table 4 (around 31% of the sample). We also define a (partially) unobservable vector Q_i taking values 1 if the customer is cured and 0 otherwise, and the probability $p_l = \Pr(Q_i = 1 \mid C_i^{FLT} = l)$. The upper bound for p_l is obtained after excluding Case 1, and equals $\sup p_l = 1 - \sum_i \sum_j I[C_i = j] / \sum_i I[C_i^{FLT} = l]$ ($\forall j: \mathcal{C}_j \cap \mathcal{C}_l \neq \emptyset$). The overall integrated hazard affects the survival of the *cured* and *uncured* group, respectively

[7] The model can be extended to include left censoring, but this is not a concern in the present data setting.

$S_l(t|Q_i{=}1) = \exp(-\Sigma_{j\in\mathcal{P}^{-l}} H_j)$ and $S_l(t|Q_i{=}0) = \exp(-\Sigma_{j\in\mathcal{P}^{+}} H_j)$. With latent cure status, the survival function is a mixture, $S_l(t) = p_l\, S_l(t|Q_i{=}1) + (1-p_l)\, S_l(t|Q_i{=}0)$, since the customer may belong to either group. Three cases contribute to the likelihood in the following way:

Case 1. The customer's SLT churn occurs in time t_i and has common elements with the FLT churn ($Q_i = 0$, $\mathcal{C}_j \cap \mathcal{C}_l \neq \emptyset$): We observe the cure status. Therefore, the customer belongs to the uncured group with survival probability $\Pr(Q_i{=}0) S_l(t|Q_i{=}0)$. The contribution to the likelihood is

$$\Pr(t_i, C_i = j) = (1 - p_l)\alpha_{jl}\gamma_{jl} t_i^{\gamma_{jl}-1} \exp\left(-\sum_{r=1}^{k} \alpha_{rl} t^{\gamma_{rl}}\right).$$

Case 2. The customer's SLT churn occurs in time t_i and has no common elements with the FLT churn ($\mathcal{C}_j \cap \mathcal{C}_l = \emptyset$): The cure status is not observable, so the customer has a mixture survival function. The contribution to the likelihood is

$$\Pr(t_i, C_i = j) = \alpha_{jl}\gamma_{jl} t_i^{\gamma_{jl}-1} \left[p_l \exp\left(-\sum_{r\in\mathcal{P}^{-l}(\mathcal{S})} \alpha_{rl} t^{\gamma_{rl}}\right) + (1 - p_l) \exp\left(-\sum_{r=1}^{k} \alpha_{rl} t^{\gamma_{rl}}\right)\right].$$

Case 3. The customer does not churn in the observation period ($C_i{=}0$): The cure status is not observable. The likelihood contribution of a censored observation is the mixture survival function (expression in outer brackets of Case 2).

To compute the hazard rates for Cases 1 and 2, we have used the relation $H = -\log(S)$ and $h = \partial H/\partial t$. For customer *i*, who churned due to competing risk *l* in the FLT, the likelihood contribution is constructed by combining the three different ways in which the SLT can end (Cases 1-3):

$$L_{il}\left(t_i, C_i \middle| C_i^{FLT} = l\right) = h(t_i, C_i = j)^{\delta_{ij}} \times \left[(1-\delta_{il})p_l \exp\left(-\sum_{r\in\mathcal{P}^{-1}(\mathcal{S})} \alpha_{rl} t_i^{\gamma_{rl}}\right) + (1-p_l)\exp\left(-\sum_{r=1}^{k} \alpha_{rl} t_i^{\gamma_{rl}}\right)\right] \tag{M2}$$

where $j \neq l$, $\delta_{il}=I[\mathcal{C}_j \cap \mathcal{C}_l \neq \emptyset]$, and $\delta_{ij}=I[C_i=j]$.

Capturing the Effects of Marketing and Customer Behavior

Since the SLT covariates are observed monthly, the survival probability can be reformulated as a product of survival functions evaluated over all months the customer maintained service ($C_{it}=0$). For the month t when churn is observed, and $C_{it} = j$, the hazard is evaluated on period $[t_{a-1}, t_a)$, for details see Seetharaman and Chintagunta (2003). Therefore, the likelihood of the competing risks model (M1) rearranged in the discrete time setting to include time-varying covariates is:

$$L_i(t_i, C_{it}) = \left(1 - \exp\left(-l\left(x_{it_{a_i}}\right)\int_{t_{a_i}-1}^{t_{a_i}} h_j(u)du\right)\right)^{\delta_{ijt}} \prod_{v=1}^{a_i-\delta_i} \exp\left(-l(x_{iv})\sum_{r=1}^{c}\int_{t_{v-1}}^{t_v} h_j(u)du\right) \tag{M1X}$$

where $\delta_{ijt}=I[C_{it}=j]$, $\delta_i=\Sigma_j\Sigma_t\delta_{ijt}$.. Under Weibull specification, the integrals in (M1X) have a closed form. Finally, the discrete-time mixture-cure competing risks model with covariates has a likelihood of the form:

$$L_i(t_i, C_{it}) = \left(1 - \exp\left(-l\left(x_{it_{a_i}}\right)\int_{t_{a_i}-1}^{t_{a_i}} h_j(u)du\right)\right)^{\delta_{ijt}} \times \prod_{v=1}^{a_i-\delta_i}\left[(1-\delta_{il})p_l \exp\left(-l(x_{iv})\sum_{r\neq l}\int_{v-1}^{v} h_r(u)du\right) + (1-p_l)\exp\left(-l(x_{iv})\sum_{r=1}^{c}\int_{v-1}^{v} h_r(u)du\right)\right] \tag{M2X}$$

where the indicators have been defined previously. Here the Weibull scale parameter α_{jl} becomes a cause-specific intercept $\exp[\log \alpha_{jl}, l(x_{it})]$, and $l(x_{it})$ is a linear predictor

$$
\begin{aligned}
l(x_{it}) = {} & \beta_1 SLT\_revenue_{it} + \beta_2 SLT\_xbuy_{it} + \beta_3 SLT\_xbuy_{it}^2 + \beta_4 SLT\_refer_{it} + \beta_5 SLT\_comp_{it} \\
& + \beta_6 SLT\_reco_{it} + \beta_7 SLT\_call_{it} + \beta_8 SLT\_email_{it} + \beta_9 SLT\_dmail_{it} \\
& + \beta_{10} SLT\_call_{it} * SLT\_email_{it} + \beta_{11} SLT\_call_{it} * SLT\_dmail_{it} \\
& + \beta_{12} SLT\_email_{it} * SLT\_dmail_{it} + \beta_{13} SLT\_win\_promo_{it} + \beta_{14} taway \\
& + \beta_{15} taway^2 + \beta_{16} FLT\_tenure + \beta_{17} FLT\_revenue + \beta_{18} gender + \beta_{19} age \\
& + \beta_{20} income + \beta_{21} hhold + \beta_{22} educ
\end{aligned} \tag{1}
$$

which measures the effects of customer service and behavior characteristics and marketing actions on repeat churn behavior, leveraging the panel data structure.

Identifying Cured and Uncured Groups

The cure probability p_l can be parameterized using the information available to the firm at the time of reacquisition to identify the characteristics of customers with high cure probability. Similar to other marketing applications of MC models (Sinha and Chandrashekaran 1992; Srinivasan, Lilien, and Rangaswamy 2006) we use a logit link

$$
\begin{aligned}
\log \frac{p_l}{1 - p_l} = {} & \lambda_{1,l} FLT\_tenure + \lambda_{2,l} FLT\_revenue + \lambda_{3,l} FLT\_xbuy + \lambda_{4,l} FLT\_xbuy^2 \\
& + \lambda_{5,l} FLT\_refer + \lambda_{6,l} FLT\_comp + \lambda_{7,l} FLT\_reco + \lambda_{8,l} FLT\_call \\
& + \lambda_{9,l} FLT\_email + \lambda_{10,l} FLT\_dmail + \lambda_{11,l} FLT\_call * FLT\_email \\
& + \lambda_{12,l} FLT\_call * FLT\_dmail + \lambda_{13,l} FLT\_email * FLT\_dmail + \lambda_{14,l} gender \\
& + \lambda_{15,l} age + \lambda_{16,l} income + \lambda_{17,l} hhold + \lambda_{18,l} educ + \lambda_{19,l} win\_pri \\
& + \lambda_{20,l} win\_ser
\end{aligned} \tag{2}
$$

Identification concerns arise in this setting because for 31% of the sample, the membership to cured and uncured groups is latent. The issue of identification in mixture cure models has been discussed in the single-risk case (Farewell 1982; Yu et al. 2004), and recently in competing risks (Basu and Tiwari 2010). We take several steps to alleviate the identification issue. First, favoring parsimony over model complexity, the mixture survival functions defined here assume equal churn-specific hazards in the two groups. This solution imposes that the overall hazard is always lower in the cured group than in the uncured one and was proposed by Basu and Tiwari (2010). Second, we assume homogeneity in effects of SLT customer behavior and marketing actions on customer SLT duration. This is not a strong assumption, since Kumar, Bhagwat, and Zhang (2015) did not find empirical support for customer heterogeneity in their model of SLT duration. Third, unlike previous studies (Sinha and Chandrashekaran 1992; Srinivasan, Lilien, and Rangaswamy 2006), we use separate variable sets for modeling the cure probability (Equation 2) and duration (Equation 1) to increase data variability and alleviate possible collinearity (demographic variables enter both equations). Lastly, we have collected a large sample to ensure that there are customers dropping-out in every period due to all reasons[8]. We have observed that estimating the model with poor starting points occasionally causes computational issues. Therefore, we estimate the simple models (M1 and M2) first, and use their solutions to initiate the estimation of the more complex models (M1X and M2X(L)). Finally, we simulate model parameters and are able to recover them with very little deviations.

Addressing Endogeneity

Firms strategically decide about the intensity of marketing variables to each customer M_{it}= [call2$_{it}$, email2$_{it}$, dmail2$_{it}$]. Since we do not have the entire information about all inputs that go into this decision process, omitted variables may cause a correlation between marketing communications M_{it} and the error term in the SLT churn equation. To address this endogeneity, we use a control function approach (Petrin and Train 2011), which depends on the quality of the instrumental variables (IVs). They should be related to the intensity of marketing communications but not influence the customer's decision to churn. We use three instruments: the average number of emails, direct mails, and phone calls made to customers' peers. We define peers as those customers who are in the same revenue bracket as the focal customer for the

[8] Since the model supports periods of different lengths, we have aggregated periods when no churn is observed. However, this happens only at the beginning of the time horizon.

current period. Peer-based instruments have been used by German, Ebbes, and Grewal (2015) to investigate implications of CMO presence on the firm performance. We believe that the proposed IVs are relevant and valid. First, we argue that the level of marketing communications to peers is correlated with the level of marketing to the focal customer. Firms strategically set marketing variables to maximize profits, so marketing to the focal customer and peer customers, who are similar in generated revenue, will reflect this unobserved profit-maximizing rule. Therefore, the instruments are relevant. Regarding the validity of the IVs, we do not observe strong network effects, as the level of communications received by peers are not highly correlated (r<.10) with a customer's observed churn. Therefore, such communications are not observed by the focal customer and will not affect their decision to churn.

The control function approach requires that the endogenous variables M_{it} be written as a function of the instrumental variables, all exogenous variables entering the equation, and a vector of unobserved terms μ. Under valid instruments, μ is the only source of endogeneity in the model. Therefore, we write the following equations:

$$\begin{aligned}
&[\mathrm{SLT_call}_{it}, \mathrm{SLT_email}_{it}, \mathrm{SLT_dmail}_{it}] \\
&\quad = \pi_{1,k}\mathrm{AvgPcall}_{it} + \pi_{2,k}\mathrm{AvgPemail}_{it} + \pi_{3,k}\mathrm{AvgPdmail}_{it} \\
&\quad + \pi_{4,k}\mathrm{AvgPcall}_{it} * \mathrm{AvgPemail}_{it} + \pi_{5,k}\mathrm{AvgPcall}_{it} * \mathrm{AvgPdmail}_{it} \\
&\quad + \pi_{6,k}\mathrm{AvgPemail}_{it} * \mathrm{AvgPdmail}_{it} + \pi_{7,k}\mathrm{SLT_revenue}_{it} \\
&\quad + \pi_{8,k}\mathrm{SLT_xbuy}_{it} + \pi_{9,k}\mathrm{SLT_xbuy}_{it}^2 + \pi_{10,k}\mathrm{SLT_refer}_{it} \\
&\quad + \pi_{11,k}\mathrm{SLT_comp}_{it} + \pi_{12,k}\mathrm{SLT_reco}_{it} + \pi_{13,k}\mathrm{SLT_win_promo}_{it} \\
&\quad + \pi_{14,k}\mathrm{taway} + \pi_{15,k}\mathrm{taway}^2 + \pi_{16,k}\mathrm{FLT_tenure} + \pi_{17,k}\mathrm{FLT_revenue} \\
&\quad + \pi_{18,k}\mathrm{gender} + \pi_{19,k}\mathrm{age} + \pi_{20,k}\mathrm{income} + \pi_{21,k}\mathrm{hhold} + \pi_{22,k}\mathrm{educ} \\
&\quad + \mathrm{u}_{\mathrm{it,k}},
\end{aligned} \tag{3}$$

where k={1,2,3} indicates the endogenous dependent variables, and Z_{it} = [$\mathrm{AvgPcall}_{it}$, $\mathrm{AvgPemail}_{it}$, $\mathrm{AvgPdmail}_{it}$] are the instrumental variables defined earlier. The computed residuals [$\hat{u}_{it,1}$, $\hat{u}_{it,2}$, $\hat{u}_{it,3}$] based on OLS estimation results of Equation 3 are introduced additively to Equation 1, which corrects the endogeneity issue due to omitted variables.

RESULTS

The proposed model is estimated using a maximum likelihood approach in Matlab 2016a software. We estimate all the supporting models starting from the simple competing risks model (M1), whose solution is later used to initiate the optimization of the mixture cure competing risks model (M2). In the next step, we estimate the models with time-varying covariates (M1X and M2X). The full model incorporates the cure predictors with the logit specification (Equation 2), and we refer to it as model M2XL. We report the results of model M2XL. The results of the supporting models as well as the estimation codes are available from the authors upon request.

To compare the performance of the estimated models, we compute the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC)[9]. Our estimation results support the mixture structure among returning customers, as evidenced by the AIC values (AIC_{M2}=13566.12 vs. AIC_{M1}=13718.54), indicating a better fit of model M2 over M1. This suggests that issues underlying the FLT churn can be rectified, so that a group of returning customers is not susceptible to a related SLT churn. Moreover, explanatory covariates related multiplicatively to customer hazard rate, as well as cure status predictors, offer additional insights, as indicated by the improvement in AIC values for our proposed model (AIC_{M2XL}=52948.32 vs. AIC_{M2X}=60336.98 vs. AIC_{M1X}=71724.52). Adjusting for model complexity, the BIC values also support these findings.

[9] Note that the likelihood of the model without covariates cannot be directly compared to the one including covariates, since the former is estimated on less informative data (cross-sectional), while the latter includes monthly time-varying covariates (panel-data structure obtained by dividing the time horizon into monthly intervals). Since the models are equivalent and explain the same time dependence structure, the estimates of the Weibull parameters should be similar.

We now turn our focus to estimation results of the proposed model M2XL shown in Table 5. Overall, the Weibull shape parameter estimates are significantly greater than one across all FLT and SLT churn risks, indicating a positive time dependence of the risk of defection over the SLT. That is, customers' risk of churning is consistently increasing over time, and this applies to all three SLT defection reason combinations. Previous research in CRM has recognized that hazard rates increase over time in a customer's FLT (Braun and Schweidel 2011), and our findings suggest that this also applies in the SLT. An examination of the effect of the time-varying SLT customer behavior and marketing communications on the duration of the second tenure, reveals some additional, interesting insights. Each coefficient summarizes the proportionate response of the hazard to a small change in the relevant covariate. Therefore, the negative (positive) parameters indicate that an increase in a covariate proportionally leads to decreased (increased) churn rates, which translates to longer (shorter) SLT durations.

Consistent with our expectations, we find that customers bringing more SLT revenue exhibit longer SLT tenures (β_1=-.057, p-value<.01), meaning that loyal customers pay on average higher prices (indicating higher perceived value). Regarding customer behavior, we see that customers who engage in traditionally desirable behaviors, like cross-buying (β_2=-.076, p-value<.01; β_3=.009, p-value<.05) and customer referrals (β_4=-.061, p-value<.05), also exhibit longer SLT tenures. On the other hand, customers who file more complaints (β_5=.004, p-value<.05) will have shorter SLT. Analyzing the firm's actions, we find that increased service recovery efforts (β_6=-.021, p-value<.05) have a positive association with the duration of customers' SLT, in line with our expectations. The same applies to marketing contacts, both for the main effects (β_7=-1.823, p-value<.01; β_8=-1.471, p-value<.01; β_9=-2.196, p-value<.01) and the interactions (β_{10}=-.044, p-value<.05; β_{11}=-.039, p-value<.05; β_{12}=-.012, p-value<.10). We

Table 5: Proposed Model Estimation Results

	FLT Churn: Price	FLT Churn: Service	FLT Churn: Price & Service
Mixture Cure – Predictors			
FLT Tenure	.041**	.084**	.027**
FLT Revenue	.029**	.089**	.009**
FLT Cross-buy	.922**	.126**	.082**
FLT Cross-buy^2	-.317**	-.019**	-.119*
FLT Referrals	.045**	.079**	.021**
FLT Complaints	-.077**	-.142**	-.028**
FLT Recoveries	.059**	.031**	.007**
FLT Phone calls	.388***	.066***	.046***
FLT Emails	.291***	.091***	.058***
FLT Direct mails	.177***	.143***	.043***
FLT Phone calls * FLT Emails	.165**	.009**	.069**
FLT Phone calls * FLT Direct mails	.339**	.097**	.056**
FLT Emails * FLT Direct mails	.346**	.046**	.035**
Gender	-.093**	-.027**	-.052**
Age	.002*	.041*	.001
Income	.084**	.042**	.003*
Household size	.093*	.087*	.025*
Education	.004*	.058*	.018**
Price-related win-back	.052**	.029**	.092**
Service-related win-back	.027**	.043**	-.075**
Competing Risks – Weibull Parameters			
SLT Churn: Price			
Scale	.215***	.196***	.188***
Shape	7.417***	8.922***	8.865***
SLT Churn: Service			
Scale	.191***	.168***	.153***
Shape	7.186***	8.417***	8.893***
SLT Churn: Price & Service			
Scale	.198***	.147***	.139**
Shape	7.023***	8.785***	8.927***

Competing Risks – Covariates	
SLT Customer Behavior	
SLT Revenue	-.057***
SLT Cross-buy	-.076***
SLT Cross-buy^2	.009**
SLT Referrals	-.061**
SLT Complaints	.004**
SLT Recoveries	-.021**
SLT Marketing Communications	
SLT Phone calls	-1.823***
SLT Emails	-1.471***
SLT Direct mails	-2.196***
SLT Phone calls * SLT Emails	-.044**
SLT Phone calls * SLT Direct mails	-.039**
SLT Emails * SLT Direct mails	-.012*
Controls and Demographics	
SLT Promotion	-.401**
FLT Defection period	.081***
FLT Defection period^2	-.036**
FLT Tenure	-.057**
FLT Revenue	-.039**
Gender	.018**
Age	-.062*
Income	-.155**
Household size	-.007*
Education	-.065**
Endogeneity correction	
$\hat{u}_1$	2.517*
$\hat{u}_2$	-8.447**
$\hat{u}_3$	22.928***

* p<.1, ** p<.05, *** p<.01

also find that the risk of repeat churning is significantly lower while the promotional offer perks are active (β_{13}=-.401, p-value<.05), as expected. Regarding prior churn behavior, the results indicate that the duration of the lapse period has a nonlinear relationship with the second tenure with the firm (β_{14}=.081, p-value<.01; β_{15}=-.036, p-value<.05), so that customers who accept the win-back offer early exhibit longer second tenures. Based on the estimates for the FLT tenure (β_{16}=-.057, p-value<.05) and revenue (β_{17}=-.039, p-value<.05) controls, we find evidence that customers with longer and more profitable FLTs will also tend to have longer SLTs. Looking at customers' demographics, we find that female customers (β_{18}=.018, p-value<.05), older customers (β_{19}=-.062, p-value<.10), and those with higher incomes (β_{20}=-.155, p-value<.05) and levels of education (β_{22}=-.065, p-value<.05) are associated with longer SLT durations.

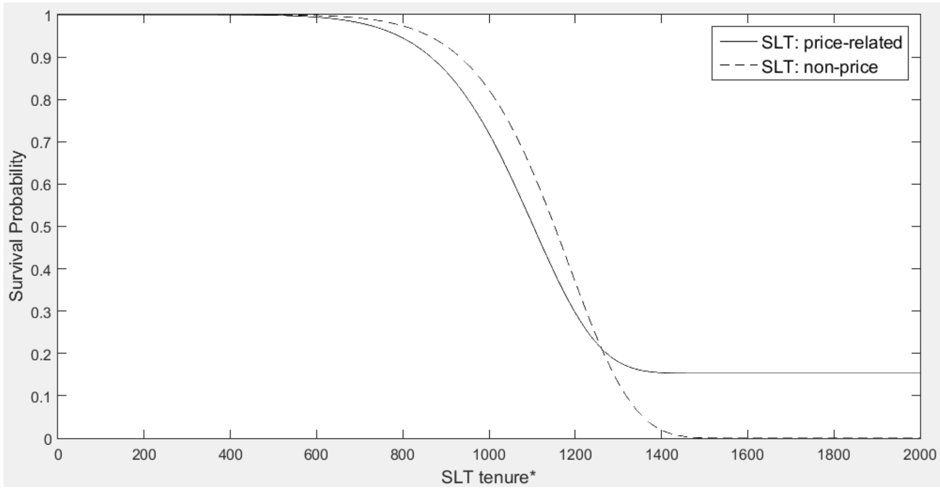
Regarding customers' membership in the cured and uncured groups, Table 5 shows the estimated effects of the FLT, demographic, and win-back predictors on the probability of being cured. Positive coefficients are associated with an increase in the likelihood of a customer being cured, while negative coefficients show the opposite effect. The direction of the effects is uniform across the different FLT churn reasons and is largely consistent with our expectations. Specifically, customers with longer tenures, and higher generated revenues during the FLT are more likely to become cured. The same applies to customers who made more successful FLT referrals. On the contrary, higher numbers of complaints decrease the chances of a customer being a member of the cured group, while service recoveries can successfully increase them. Marketing communications during the customer's FLT also have a positive relationship with their cure likelihood. This effect is enhanced when such actions are implemented through various media, as evidenced by the interactions between them. Regarding demographics, customers who are female, are older, have larger household size, and have higher income and level of education are more likely to be cured. The direction of the effects of the abovementioned characteristics and actions apply universally, regardless of the reason for the FLT churn. Finally, win-back offers including solely price incentives are associated with higher cure probabilities for customers whose FLT churn was price-related (i.e. price or price-and-service). On the other hand, customers who left only because of service issues are more likely to be cured when accepting an offer including solely service incentives.

Based on the estimates of cure predictors reported in Table 5, we have calculated the average probability for those customers to be price-cured (15.3%) and service-cured (20.4%), suggesting that that the firm has most success in addressing service issues. The propensity for customers to be both price-cured and service-cured is naturally the lowest (6.2%), as the model implies that they would never churn in their SLT. Model-free evidence provides support for this result. Since only censored observations can be potentially both price-cured and service-cured, the upper bound on this quantity is 9.94%. In other words, returning customers whose FLT churn was due to price-and-service and SLT duration is longer than four years (length of the observation window) have a high chance of being long-term customers (around 62%).

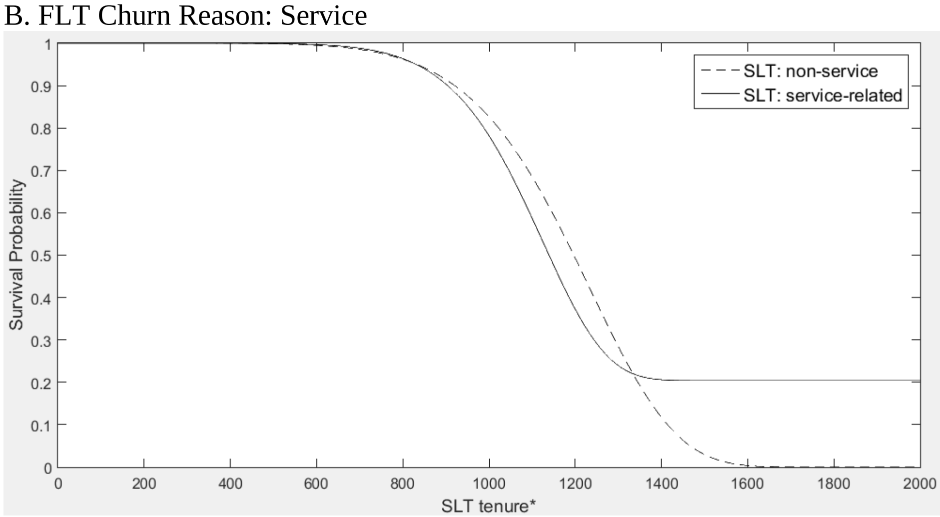
To capture time dependence in customers' repeat churn behavior, we use the average predicted cure probabilities and Weibull estimates to plot relevant cause-specific SLT survival functions. Figures 3(a-b) show two types of survival functions: an aggregate one, specific to churn categories with common elements with the FLT churn (solid line), and a survival function specific to the churn category without common elements with the FLT churn (dashed). The survival function in Figure 3c aggregates all types of churn categories. The average predicted cure probabilities are visible here as the values at which the solid lines level off. Focusing on customers whose FLT churn was attributed to a price reason, price issues are still the main cause

Figure 3: Cause-Specific Survival Probability across FLT Churn Reasons (A-C)

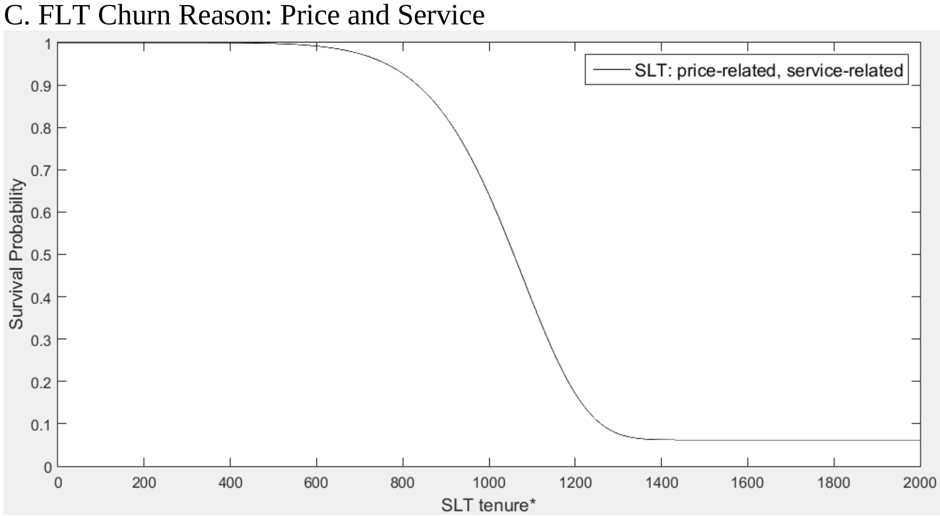
A. FLT Churn Reason: Price



B. FLT Churn Reason: Service



C. FLT Churn Reason: Price and Service



* All tenures are measured in days.

for early SLT churn, as evidenced by the solid survival curve that drops the fastest before leveling off (see panel (a) in Figure 3). This suggests that customers who churn early will do so because of price-related reasons again, despite the firm's efforts to reacquire and cure them. However, the longer a returning customer maintains the contract, the more likely they will churn for reasons other than price. A similar pattern is visible for customers who churned because of a service reason in their FLT (see panel (b) in Figure 3). In this case, service-related concerns cause the customers to repeat churn earlier than non-service-related concerns. Finally, customers whose FLT churn was because of both reasons exhibit a unique survival pattern (see panel (c) in Figure 3), which drops quickly, but levels off earlier than the previous cases. Overall, we see that price- and service-churners with short SLT tenures are more likely to churn again due to the same reason as in the FLT, suggesting that their initial concerns about the service offering remain unchanged.

Model validation

Since the focus of this study is on the time and the reason for SLT churn, we examine two related quantities for model validation: we compare the model-based predictions with the observed values for (a) retention rates and (b) proportions of churn reasons. The retention rate captures the aggregate churn pattern regardless of the reason. Evaluated in month *t*, it is the ratio of customers who maintained service throughout month *t* over those who maintained service throughout month $\mathrm{t}\text{-}1$, calculated as the fraction of two consecutive survival functions $S(\mathrm{t})/S(\mathrm{t}\text{-}1)$. Those are calculated separately for each model, as they have different survival function specifications. To assess how well the model predicts the type of churn, we first calculate the observed proportions of customers churning for each reason every month. The predicted relative churn probability of reason *j* in month *t* is the proportion of the churn-specific risk in the overall churn risk. Based on the relation between the integrated hazard and the survival function, we define it as $-\log S_j(t)/-\Sigma_l \log S_l(t)$, where S_j is the churn-specific survival function.

To validate the proposed model (M2XL) we use the calibration and a holdout sample to gauge both in- and out-of-sample predictive performance and compare it with the simpler benchmarks (M1(X) and M2(X)). To this end, we calculate the mean absolute percentage error (MAPE) for both the calibration and the holdout sample, comparing the differences between predicted and observed values. Overall, the prediction errors of the retention rates are small (less than 5% for all models in the calibration and holdout sample), with the proposed approach yielding the most accurate forecasts. The prediction errors for the proportions of churn reasons range from 16.86% (M2XL) to 24.37% (M1) in the holdout sample, and from 15.46% (M2XL) to 22.27% (M1) in the calibration sample. The findings regarding the out-of-sample predictions suggest that the inclusion of covariates in the SLT hazard and the logit probabilities leads to improved accuracy, as they capture important firm and customer behavior.

Simulation

We demonstrate how a firm can utilize the proposed approach and provide evaluations of simulated marketing policies in terms of their retention and monetary gains. To this end, we perform simulations of two types of scenarios, using the estimated results of our proposed model. First, we evaluate the cure probability of customer profiles based on their FLT history and the type of win-back they received, and then compare gains (losses) obtained from a longer (shorter) SLT tenure. Second, we explore how SLT marketing retention efforts can extend the SLT duration. In each scenario, we compute separately the median duration and profitability of customers whose FLT churn was due to price, service, and both reasons, which are shown in the columns of Table 6. The median duration is the point *t* where the survival probability is $S(t) =$

Table 6: The Impact of Reduced Repeat Churn Behavior on Duration and Profitability

	FLT: Price			FLT: Service			FLT: Price & Service[3]		
	% cured	**Median Duration (days)**	**Incremental Profit per Customer[2] ($)**	**% cured**	**Median Duration (days)**	**Incremental Profit per Customer[2] ($)**	**% cured**	**Median Duration (days)**	**Incremental Profit per Customer[2] ($)**
Benchmark strategy[1]	50%	1079	647.40	50%	1103	661.80	50%	1685	1011.00
Recovery probability									
FLT Tenure									
Low 25%	5%	1022	-34.20	0.2%	1038	-39.00	12%	1070	-369.00
Top 25%	95%	1146	40.20	99.8%	1196	55.80	88%	N/A	N/A
FLT Revenue									
Low 25%	43%	1069	-6.00	29%	1071	-19.20	48%	1255	-258.00
Top 25%	57%	1090	6.60	71%	1141	22.80	52%	N/A	N/A
Win-back									
Price	49%	1077	-1.20	50%	1103	0.00	45%	1221	-278.40
Service	47%	1075	-2.40	50%	1103	0.00	37%	1154	-318.60
Price & service	54%	1085	3.60	50%	1103	0.00	68%	N/A	N/A
SLT Marketing									
SLT Recoveries									
Remove 1/year		1079	0.00		1102	-0.60		1347	-202.80
Add 1/year		1080	0.60		1104	0.60		N/A	N/A
SLT Phone calls									
Remove 1/year		1059	-12.00		1080	-13.80		1208	-286.20
Add 1/year		1101	13.20		1128	15.00		N/A	N/A
SLT Emails									
Remove 1/year		1063	-9.60		1084	-11.40		1221	-278.40
Add 1/year		1097	10.80		1123	12.00		N/A	N/A
SLT Direct mails									
Remove 1/year		1054	-15.00		1075	-16.80		1196	-293.40
Add 1/year		1105	15.60		1133	18.00		N/A	N/A

[1] Strategy based on median values of all covariates.

[2] All incremental profits are relative to profits obtained from the benchmark strategy.

[3] The median duration is not specified for cure probabilities higher than 50% because the point .5 does not belong to the codomain of this survival function.

0.5. In other words, 50% of the population would have shorter tenures than the median value, and the other 50% will have longer tenures. To calculate profitability, we assume an average monthly revenue of $100 from each customer, and a profit margin of 18% (after the operational and marketing costs), which are representative for this industry.

The benchmark policy is one where all covariates are fixed at median values (Equation 1 and 2). The median SLT duration and customer value of this benchmark policy is shown in the first row of Table 6, and all incremental gains per customer obtained from different policy simulations are relative to the gains from the benchmark policy. We find that the median SLT duration of the benchmark policy amounts to 1,079 days for customers who churned for a price reason in their FLT, 1,103 days for service churners, and 1,685 for customers who churned due to both reasons. The median SLT profitability for the benchmark policy ranges at $647-$1101. The results of the last category (FLT churn due to price-and-service) need to be read with caution. By construction, the benchmark cure probability is 50%, achievable only when at least 50% of the sample is censored (vs. 9.94% in the current application). Furthermore, due to the specific shape of the survival function (Figure 3c) the median duration is not specified for cure probabilities higher than 50% (it would never reach the value $S(t) = 0.5$). The results of the various policy simulations are summarized in the remaining rows of Table 6.

The cure-probability-based simulations show how customer characteristics – like FLT tenure and revenue – and win-back offer allocation are related to the customer cure probability, and in turn SLT duration and profitability. When a customer accepts the win-back offer, the firm has information about their FLT and churn behavior and is able to calculate the probability the customer is cured. Profiling customers based on their FLT tenure, we see that a customer who is in the bottom 25% percentile of the FLT tenure distribution and whose FLT reason for churn was price-related will have a 5% probability of cure, a median tenure of 1,022 days, and will bring a loss of $34 compared to a benchmark customer. Based on customer cure profiling, the biggest monetary gains, amounting to $55.80, come from customers whose FLT churn was service-based and have longer FLT tenures (at the top 25% percentile). Furthermore, we find that the bundled win-back offer generally leads to a higher cure probability, and in turn longer tenure and higher profits, than single-benefit offers (even when the benefit matches the cause for FLT churn). This suggests that customers receiving a win-back offer with two perks may perceive it as more valuable than the single-benefit offers, even though all win-back offers are comparable in value.

Regarding the SLT marketing strategy simulations, we consider the following actionable policies that the firm can implement during the SLT: increasing successful recoveries and increasing the number of phone calls, emails, and direct mails per year. We found that improving successful recoveries has minimal impact on median SLT duration and profitability, up to $0.60 per customer. In contrast, the monetary gains from marketing communication adjustments are much greater, with the biggest improvement achieved by increasing the number of direct mails sent to the customer. If the firm sends one additional paper communication to retain its customers, the SLT monetary gains could range at $15-18 per customer. Implementing this policy over the entire sample would lead to incremental gains of $150,000 over the customers' SLT. For a firm that loses a million customers due to second churn every quarter, the overall incremental gains can result in increasing the SLT profitability by more than $15 million.

DISCUSSION

This study investigates the SLT of returning customers in order to enhance retention strategies. Using a novel modeling approach to handle the intricacies of the SLT, we study customers' SLT churn behavior, which includes the timing and reason for such churn. The findings suggest that customers' defection motives are not consistent, as the reasons for FLT and SLT churn are generally different and exhibit varying time-dependence. Specifically, among the customers who lapsed because of price (service) concerns in the FLT, those who terminate their SLT early tend to churn due to price (service) again. In contrast, those who terminate their SLT later are more likely to churn because of other reasons, suggesting that customers' churn patterns change over time. We measure the effect of contemporary customer behavior and marketing activities on the SLT duration and repeat churn behavior and find that overall customers' positive SLT experience is related to longer SLT tenures. Furthermore, firm-initiated contacts are the backbone of a retention strategy in the SLT, showing an ability to substantially extend tenures and consequently bring profit. We find evidence that there are two types of returning consumers. The first group is composed of individuals who can defect due to any reason (uncured customers), and the other includes individuals who are susceptible to fewer types of churn (cured customers) because they are satisfied by the firm's efforts to improve aspects of the service. Griffin and Lowenstein (2001) recommend developing internal criteria for a routine segmentation of customers based on their reacquisition probability and expected SLTV. We further recommend refining such segmentation criteria by accounting for customers' cure probability, which we show impacts their SLT profitability as well.

The findings of this study enable managers to design retention strategies for the SLT based on the relation of customer-specific behaviors and marketing activities with the SLT duration and repeat churn behavior. This offers a tool to track in real time which customers are at risk of churning again, when, and why. Using current data allows the firm to build proactive retention strategies aimed at customers who are most at risk of churning again and intervene at the right time in their SLT. The findings suggest that marketing communications through a variety of media can extend customers' SLT. This study also aids in segmentation of returning customers based on their cure potential. By incorporating the cure predictors, it enables the firm to leverage its knowledge about customers' FLT and recognize which reacquired customers have a high potential of becoming long-term customers. Naturally, firms want to make the most out of their reacquisition efforts, and we show that responding to and amending the issues that led to FLT churn can convert lost customers not only to reacquired but also cured customers.

The findings of this study are subject to a few limitations, and this research can be extended in several directions. The framework can accommodate any number of unique event types, but we advise caution in high-dimensional problems, as the model exhibits exponential complexity. Planning the research, one should first conceptualize which event types are mutually exclusive, and group similar motives. Complexity issues can be alleviated by redefining the rules on the risk sets to restrict unfeasible combinations, or to focus on two-element combinations only. We also take the perspective of a single firm, and therefore cannot control for competitive actions or for customers' behavior during lapse period. Neither do we observe reasons why customers come back besides the firm's efforts. We assume there is a degree of opportunism driving their return decisions, which can be lower for cured customers. However, this reflects the information that managers have at their disposal when a customer is reacquired.

Due to data limitations, the individual influence of price and service churn is not estimated because the third type of churn is a combination of the two. Also, win-back offers are standardized for all customers, which prevents extensive testing of incentive variations. Firms can potentially tailor the offers based on each customer's CLV, and the current research does not examine whether there is a differential impact on their SLT. Additionally, churn decisions may depend on the service usage, causing endogeneity in the consumer behavior. Future research could examine this issue by interacting relevant consumer behavior variables with time. The model could also include SLT variables as cure predictors. Finally, the proposed model could be used in applications with heterogeneity in hazard parameters across the two groups. Being mindful of the abovementioned limitations, we can still gain valuable insights into customers' repeat churn behavior.

CHAPTER 3 – ESSAY 2:

MANAGING AND EVALUATING CUSTOMERS IN AN INTEGRATED CONTRACTUAL AND NONCONTRACTUAL PURCHASE SETTING

INTRODUCTION

Managing and evaluating customers is a top priority for any customer-centric organization. Research in the area of customer equity, at the aggregate level, and customer lifetime value, at the individual level, is abundant with models designed to help with such customer valuation. Two distinct trends of such efforts include models that are generally applicable to industries with either contractual or noncontractual relationship settings. In contractual settings, customers are typically under contract, so the research focus lies on predicting either customer retention (as the duration of the contract) or churn (as the time of contract termination). In noncontractual settings, where customers are not under contract, research aims to predict either customers' interpurchase time (as the duration between two consecutive purchases) or their purchase probability (as the probability to make a purchase within a certain time period).

It should be noted that the terms *contractual* and *noncontractual* purchases used in this study are also interchangeable with the terms *subscription* and *non-subscription* purchases. That is, the focus lies on the nature of the customer relationship, not on the limitations imposed by a contract. Thus, we operate under the assumption that customers are not penalized for dissolving a contract.

Firms that operate in industries where purchase settings are clearly defined can follow any of the established approaches to predict their customers' purchase behaviors, as long as the setting is either contractual (e.g., Thomas, Blattberg, and Fox 2004; Kumar, Bhagwat, and Zhang

2015) or noncontractual (e.g., Reinartz and Kumar 2003; Venkatesan and Kumar 2004). However, it is not as straightforward for a firm to effectively manage and evaluate its customers when it offers various purchase options that may or may not include a contract or subscription. In such cases, customers may have the option to gain continuous access to a service through a membership, access to a service only for particular instances through standalone access purchases, or even both. Given such purchase options, customers' purchase propensities for subscription services and for non-subscription services may vary. We argue that these two purchase propensities are driven by their underlying, or latent, relationship commitment towards the firm's services. From the firm's perspective, this relationship commitment is unobserved. The actual customer purchases, however, are observed and documented. Thus, managers can use this information to uncover the level, or state, of this latent relationship commitment.

Differentiating between the two purchase propensities and understanding the underlying process that drives them enables firms to assess and predict more accurately customer behavior and value. To accomplish this, this study aims to answer the following research questions as they apply in such a mixed contractual and noncontractual setting:

1. How do latent relationship commitment states influence customers' purchase behaviors?
2. Do the two customer purchase behaviors influence each other?
    a. How are contractual purchase characteristics, like value and contract length, related to the value of noncontractual purchases?
    b. How are noncontractual purchase characteristics, like value and bundle size, related to the value of contractual purchases?
3. How to assess the value of a customer to the firm?

This study contributes to the marketing literature and practice in the following ways. It provides a framework of customers' purchasing behavior regardless of the purchase setting. The proposed model is applied on data from the fitness industry, but it is generalizable to other services with mixed contractual and noncontractual purchase components. For example, it can be applied to telecommunications, where wireless providers offer contractual and noncontractual accounts, as well as add-on products (international calls, text packages, roaming, etc.). This research also provides a managerial tool to measure the lifetime value of customers in this setting and, based on this information, to identify profitable customers. Thus, it has strategic implications for targeting of marketing programs aiming to improve customer retention.

MODELING CONTEXT

In a mixed relationship setting, i.e. where the customers have the option of purchasing contractual and/or noncontractual services, they may purchase an access membership, standalone access passes, or both. The two types of purchases are conceptually different because they express customer relationship commitment in different ways. This does not imply a higher or lower level of commitment, but rather a preference for either more or less structure in their relationship with the firm. A contract provides a higher level of structure, as customers under contract are committed to the relationship in a more controlled way over the period of the contract. In contrast, standalone access purchases provide a lower level of structure, as such services are more flexible in nature. Thus, it is important to distinguish between the two types of purchase propensities, which manifest through the two purchase types. These purchase behaviors may be conceptualized as the customer perspective of their interaction with the firm, being either relation-oriented (contractual) or transaction-oriented (noncontractual). This notion is equivalent to a relational vs. transactional approach of the firm in managing its customer interactions.

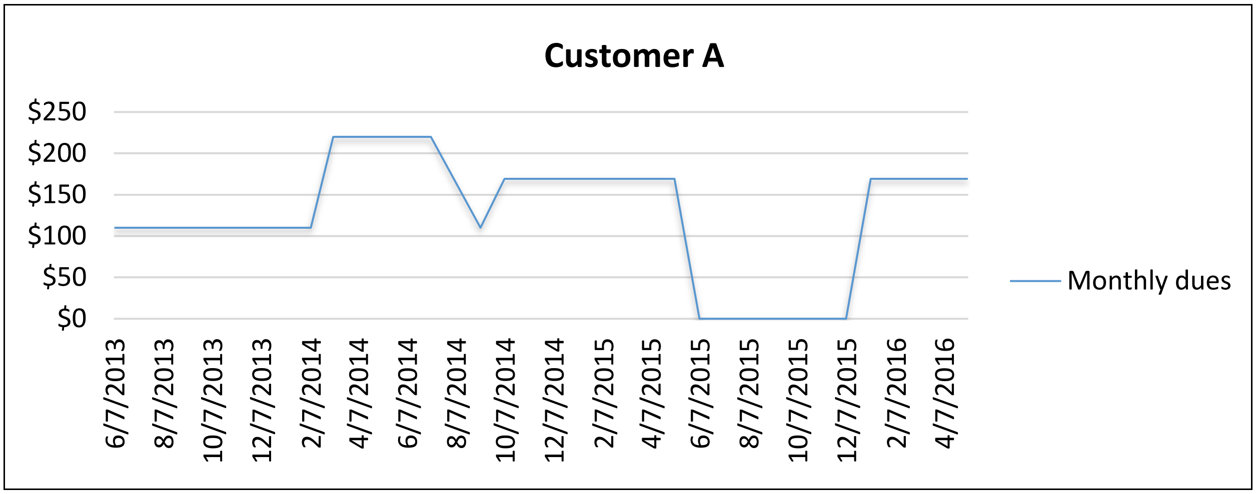
Customers exhibit varying levels of intensity of each type of relationship commitment and the equivalent type of purchase. Some customers prefer buying standalone services, others opt for a membership, while others purchase both to varying degrees. In other words, each of the purchase types – contractual and noncontractual – might indicate varied levels of commitment, as expressed by the purchase volume – short or long contract, few or many access passes – but they still show distinct types of commitment – high and low structure. For example, a customer may have low levels of high-structure commitment (i.e. short-term contract) and high levels of low-structure commitment (i.e. large bundle purchases). Capturing such heterogeneity allows for more accurate assessment of customers' behavior and their value for the firm.

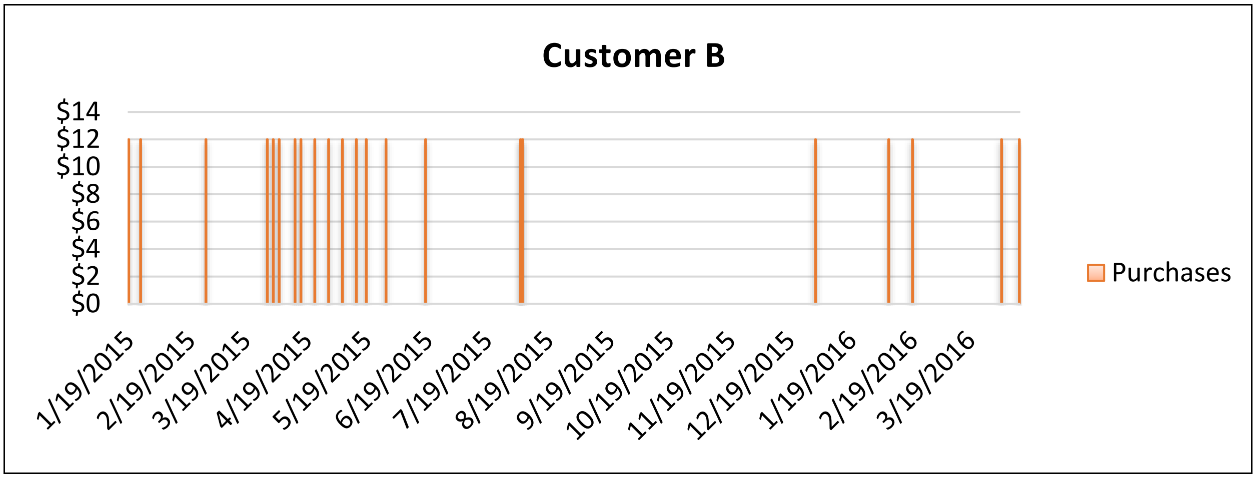
The health and fitness industry

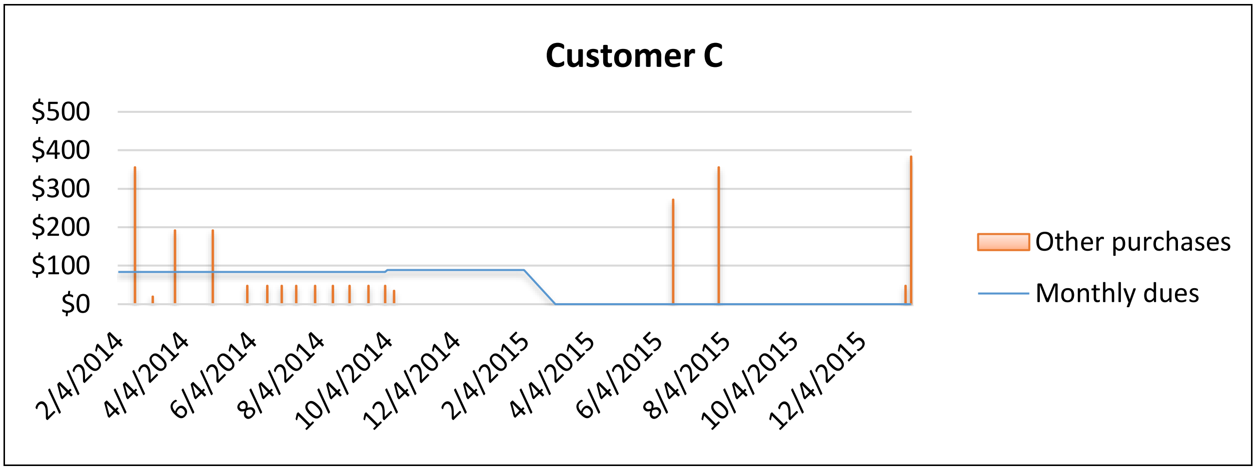
One relationship setting where both types of purchases are encountered is the health and fitness industry. An increasing importance is being placed on fitness and health in contemporary culture, which has culminated to a thriving fitness industry. Although health and fitness clubs are experiencing growth (Cohen 2017), they are still faced with problems in customer retention, like any other business. In order to combat this, managers need to be able to interpret customers' commitment to the relationship with the firm as shown through their purchases. Three sample timelines of diverse customer purchase histories are shown in Figure 1 to illustrate the purchase profiles of customers in this context.

Figure 1 showcases this interesting relationship setting which is the result of the firms in this industry offering a multitude of purchase options in order to cater to customers' highly diverse needs. One key observation about the types of relationships in this industry is that any of four different combinations may be exhibited. Following are these relationship combinations along with examples of other industries where a particular relationship is typically encountered:

Figure 1: Customer Purchase History Examples in the Health and Fitness Industry







- Pure contractual relationship (e.g. internet services)
- Pure noncontractual relationship (e.g. retail purchases)
- Relationship that starts off as contractual and then noncontractual purchases are introduced (e.g. cable services)
- Relationship that starts off as noncontractual and then a contractual element is introduced (e.g. fitness services)

Thus, the current study focuses on the fitness industry, but the approach is generalizable to any industry, with either single or mixed relationship structures.

MODEL DEVELOPMENT

The nature of customers' purchase behaviors

The two types of purchase behaviors, contractual and noncontractual, are distinct but *related*. Specifically, contract decisions are affected by prior standalone purchases and standalone purchase decisions are affected by prior contract. Both purchase behaviors manifest the customers' purchase propensities, which are driven by their underlying commitment level. Given the presence of the two purchase behaviors, an appropriate model for this relationship setting should account for the dependency between the two purchase processes.

Customers' varying levels of commitment to the service, which are easily expressed through the variety of purchase options available, result in considerable unobserved *heterogeneity* in terms of their purchase behaviors. In the current context, for example, some customers work out intensively while others engage in exercise sparsely. Some customers prefer using special exercise equipment while others prefer training through trainer-administered classes. Therefore, customers may belong to one of a few different segments corresponding to their underlying relationship state. Customers within each segment or state may exhibit distinct purchase patterns, which would be better represented by different distributions. Thus, such heterogeneity should be accounted for.

Customers purchase behaviors are not static but evolve over time in various ways. First, their consumption intensity might change. For example, a customer might exercise more over a period of a few months and then become less active, or vice versa. Second, customers' preferences for the type of service they use might change. That is, a customer might switch from trainer-administered classes to exercise through equipment or both, or from a monthly subscription to a class-by-class purchase pattern. Therefore, customers' purchase patterns, and their underlying relationship commitment, are *dynamic*.

Hidden Markov Model (HMM)

Since a customer's dynamic relationship commitment is not directly observed, a hidden Markov model (HMM) is appropriate. A HMM is a stochastic model that can be applied to time-series observations, which in this case are the purchase behaviors. It captures the relationship commitment levels as latent states, the transition between these latent states, and their connection to the observed purchase behaviors. HMMs have been used regularly in recent literature (e.g., Netzer el al. 2008, Montoya et al. 2010, Kumar et al. 2011, Ascarza and Hardie 2013, Zhang et al. 2017) to study the customer-firm relationship.

Customers in each state are different, and thus their purchases will follow different patterns, which may be best represented by different distributions. HMM accommodates this by supporting a different distribution for each state, known as state-dependent distributions. Thus, the choice of the applicable distribution for each customer is determined by their state membership. Additionally, customers can move to different states over time, according to the changes in their purchase patterns, and this is also accommodated by the HMM structure. Both the state membership and a state change are not directly observed but are inferred from the outcome of the state-dependent process.

Moreover, the HMM can be used to identify the customer-firm relationship, as this process can reasonably support the limited horizon assumption or Markov property. According to this assumption, the probability of being in a state at time *t* depends only on the state at time *t*−1 (see Zucchini and MacDonald 2009, p. 16, for a concise definition). The underlying intuition is that the state at time *t* represents "enough" summary of the past to reasonably predict the future. Here, we can assume that a customer's relationship state at time *t* is only dependent on their state at time *t*-1 which is reasonable, as the previous relationship state has merit in providing additional insights into the customer's attitude about the service while historical information from beyond time *t-1* becomes less relevant.

The underlying commitment states – Markov chain states (S)

The customer's underlying commitment state will influence their purchase propensities, which are realized through the two types of purchases they make: contractual and noncontractual. Let S_{it} be the random process representing customer *i*'s commitment with the relationship with the firm at time *t* (*t*=1, …, T_i). As a Markov chain, it allows for serial dependence in the purchase choices, by conditioning the current state on the previous state, i.e., for any *i*

$$P\left(S_t|\boldsymbol{S}^{(t-1)}\right) = P(S_t|S_{t-1})\,, t = 2, 3, \ldots, T_i\,.$$

The state transitions – transition probability matrix (Q)

Customers stochastically transition among the underlying commitment states. We can assume that a customer may transition from one state to any other state at any time *t*. An alternative approach would be to allow only for transitions to adjacent states or a potential dormancy state, applying a random walk process as in Netzer el al. (2008). For states 1, 2, …, n, the transitions from *t*-1 to *t* are:

$$\mathrm{Q}_{i,t-1\rightarrow t} = \begin{bmatrix} q_{it11} & q_{it12} & \cdots & q_{it1n-1} & q_{it1n} \\ q_{it21} & q_{it22} & \cdots & q_{it2n-1} & q_{it2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ q_{itn1} & q_{itn2} & \cdots & q_{itnn-1} & q_{itnn} \end{bmatrix}.$$

The elements in the transition matrix are the conditional probabilities that customer *i* transitions from state *s* at time *t*-1 to state *s'* at time *t*, i.e. $q_{itss'} = P(S_{it} = s' | \, S_{it-1} = s)$. These can be modeled using a multinomial logit model, so that:

$$q_{itss'} = \frac{\exp(h_{its})}{\sum_{k=1}^{n} \exp(h_{itk})}$$

where

$$h_{its} = \gamma_{ss'} + D_{it}\theta_{s'}, \forall s = 1 \dots n.$$

In the above, $\gamma_{ss'}$ is the intrinsic value of the transition from state *s* to state *s'*, $\theta_{s'}$ denotes the marginal effect of covariates in transitioning to state s', and D_{it} are the covariates associated with the transition from state *s* to *s'* for customer *i* at time *t*. We assume that the customer's relationship state will be influenced by the firm's marketing, represented here by promotional deals used by the customer, of both contractual and noncontractual type.

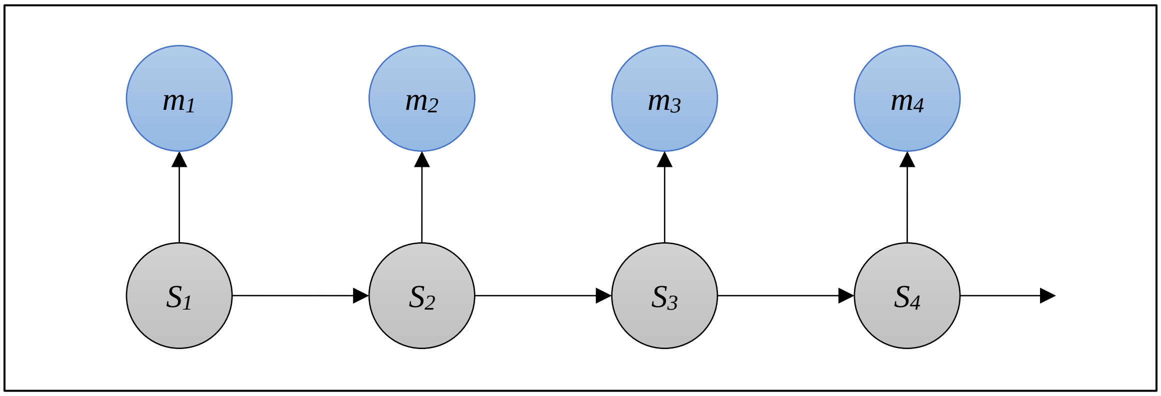
The initial state distribution (π)

The initial state distribution is the probability that customer *i* is at commitment state *s* at the beginning of their relationship, i.e. at *t*=1,

$$P(S_{i1} = s) = \boldsymbol{\pi}_i.$$

In this application, we assume that the customer's initial state is the lowest state, therefore π_i=[1,0,..,0].

Figure 2: The Evolution of Customer Relationship States (S) and Customer Purchases (m)



The state-dependent purchase behaviors (m)

We differentiate between the two types of purchases, contractual and noncontractual, but model their evolution jointly. This is important in the current context because customers' relationship state (commitment) affects both types of purchases, in a heterogenous way. Every period *t*, customer *i* decides whether and how much to spend on contractual and noncontractual fitness services. In this setting, we denote *j*=1 for contractual purchases and *j*=2 for noncontractual purchases, and time is defined on a monthly basis. Let y^*_{ijst} be customer *i*'s purchase propensity or latent utility of type *j* purchase at time *t*, given their commitment state *s*, such that

$$y^*_{ijst} = \alpha_{js} + X_{1it}\beta_{1j} + X_{2it}\beta_{2j} + Z_i\delta_j + \varepsilon_{ijt}.$$

In the above, α_{js} is the level of intrinsic value of purchase type *j* in commitment state *s*; X_{1it} and X_{2it} are customer *i*'s contractual and noncontractual transactions in period *t*; β_{1j} and β_{2j} represent the effect of those transactions on the utility of type *j* purchase; Z_i are individual-specific covariates; and δ_j measures their effect on the utility of purchase of type *j*. ε_{ijt} is the random error from a bivariate distribution

$$\begin{bmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \end{bmatrix} \sim \mathrm{N}\,[0, \Sigma], \qquad \Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_{12} \\ \sigma_1\sigma_2\rho_{12} & \sigma_2^2 \end{pmatrix},$$

which allows us to capture the dependence in contractual and noncontractual purchases.

Note that the latent utility y^*_{ijst} is not directly observed, unless it becomes positive and manifests through an actual purchase

$$y_{ijst} = \begin{cases} y^*_{ijst} & \text{if } y^*_{ijst} > 0 \\ 0 & \text{if } y^*_{ijst} \leq 0. \end{cases}$$

The state-dependent process $m_{it} = [y_{1ist}, y_{2ist}]$ is only dependent on the customer's current relationship state, i.e., for any i

$$P\left(\boldsymbol{m}_t | \boldsymbol{m}^{(t-1)}, \boldsymbol{S}^{(t)}\right) = P(\boldsymbol{m}_t | S_t)\ , t = 1, 2, \dots, T_i\ .$$

Thus, conditioning on the current state, allows for estimating the customers' purchases, without the need for information about the customer's prior relationship states or prior purchases. This is illustrated in Figure 2.

Likelihood

The likelihood of the proposed model is constructed by considering four cases that correspond to four purchase patterns within a certain month based on the purchases exhibited. Specifically, customers may a) make no purchase, b) purchase only contractual services, c) purchases only noncontractual services, or d) purchase both service types. This leads to the likelihood function being a combination of the four resulting regions, such that

$$L_i(y_{i1}, y_{i2}, \dots, y_{iT_i}) = \sum_{s_1=1}^{n} \sum_{s_2=1}^{n} \dots \sum_{s_{T_i}=1}^{n} \left(\boldsymbol{\pi}_i \prod_{t=2}^{T_i} q_{itss'} \prod_{t=1}^{T_i} \prod_{r=1}^{4} L_{rits_t}^{I_{rit}} \right)$$

where L_{rits_t} is the likelihood for each of r = 1, 2, 3, 4 cases defined in line with Kumar et al. (2011).

Customer Lifetime Value (CLV)

We can leverage the results of the model estimation to calculate the CLV for each customer as

$$CLV_i = \sum_{t=0}^{T} \left[\frac{\widehat{CP}_{ist} + \widehat{NCP}_{ist} - \widehat{MC}_{it}}{(1+d)^t} \right].$$

In the above, CLV_i is the CLV for customer i, calculated over T periods, $\widehat{CP}_{ist}$ are the profits resulting from customer's contractual purchases given state *s* at time *t*, $\widehat{NCP}_{ist}$ are the profits resulting from customer's noncontractual purchases given state *s* at time *t*, $\widehat{MC}_{it}$ are the firm's marketing costs for customer *i* at time *t*, and d is the discount rate for each time period *t*. Contractual profits ($\widehat{CP}_{ist}$) and noncontractual profits ($\widehat{NCP}_{ist}$) are obtained through the predictions of the state-dependent purchase behaviors, i.e., $\hat{y}_{\mathrm{ijst}}$.

DATA

This study uses a large data set from a variety of fitness service retailers in the US. Specifically, a sample of 1,857 customers of five fitness studios is monitored from June 2013 to June 2016. The available information includes records of customers' transactions and visits over the three-year period. Additionally, geographical information (customer location) as well as date of acquisition are also available on a customer basis. The services offered by the businesses in the sample encompass a variety of memberships (contractual) and class or limited access (noncontractual) purchases. Thus, all relevant transactions in the sample are categorized as one of the two types of purchases. All services that entail memberships, ranging from two weeks to one year, are coded as contractual. All other services, which entail access to classes, either single or multiple, are coded as noncontractual. For each customer, an observation per month is generated, resulting in a monthly interval unit of analysis.

Table 1: Variable Operationalization and Descriptive Statistics

Variable	Operationalization	Mean	Std. Dev.
Contractual	**(Varying by Month)**		
Cross-Buying	The number of different membership service types the customer is subscribed to	1.200	0.535
Tenure	The time in days from the customer's acquisition date to their latest contractual purchase	775.19	628.33
Contract Length	The length of the membership services the customer is subscribed to in months	8.143	6.059
Promotion Usage	An indicator of whether the customer uses a promotional deal (1=usage, 0=no usage)	16.8%	89.0%
Purchase Frequency	The total number of distinct purchase occasions of membership services	1.247	0.675
First Purchase	An indicator of the customer's first membership purchase (1=first purchase, 0=subsequent purchase)	4.5%	20.7%
Noncontractual	**(Varying by Month)**		
Cross-Buying	The number of different class service types the customer purchases	1.213	0.623
Tenure	The time in days from the customer's acquisition date to their latest noncontractual purchase	347.88	578.23
Bundling	The average bundle size of class services the customer purchases (0=no bundle)	0.166	0.488
Promotion Usage	An indicator of whether the customer uses a promotional deal (1= usage, 0=no usage)	35.0%	98.8%
Purchase Frequency	The total number of distinct purchase occasions of class services	1.863	1.580
First Purchase	An indicator of the customer's first class purchase (1=first purchase, 0=subsequent purchase)	35.7%	47.9%

Since this study focuses at predicting customers' purchases, we first examine basic descriptive statistics of the two purchase types. The mean monthly value of contractual purchases amounts to \$149.13, with a standard deviation of \$225.06. The mean monthly value of noncontractual purchases amounts to \$115.24, with a standard deviation of \$341.31. Although the average revenues generated through the two types of purchases are not substantially different, we see that noncontractual purchases exhibit considerably greater variance. Moreover, the median monthly contractual purchases are $110, while the median monthly noncontractual purchases are $24. These results show that customers' two distinct purchase propensities are indeed disparate and clearly do not follow the same distribution. This provides initial empirical evidence for the need to study each purchase type separately.

Drivers of Customer Value

Consistent with prior research on customer equity and CLV (e.g., Reinartz, Thomas, and Kumar 2005, Venkatesan and Kumar 2004), several descriptors of the customers' relationship are considered as drivers of customers' purchase propensities for each type of purchase. Using the transaction records, a variety of variables – including cross-buying, tenure, bundling and contract length, promotion usage, purchase frequency, and first purchase indicator – are operationalized as described in Table 1. These variables are defined and adapted accordingly for contractual and noncontractual services. Both sets of variables are used as covariates in both purchase propensity equations, as indicated in the model section, to investigate both the own-effects and the cross-effects of the relationship characteristics on the two purchase types.

RESULTS

The proposed model is estimated by maximum likelihood on the abovementioned data in Matlab 2016a software. Prior to estimation, the two dependent variables of interest are transformed by scaling the contractual and noncontractual purchase amounts by 1/100, to decrease potential computational burden or errors that larger numbers might cause. Due to the structure of HMMs, the number of latent states needs to be predetermined before estimating the model, so models with both two and three states are estimated. The two-state model exhibits the best performance based on the Akaike Information Criterion (AIC) and the Bayesian Information

Criterion (BIC), so the following discussion focuses on this model and its parameter estimation results are reported in Table 3.

The first state of the estimated model is called the “low” state and the second state is called the “high” state, as the state-dependent purchase amounts in the latter are higher than in the former by construction. This restriction is imposed on the level of intrinsic value of both purchase types, such that $\alpha_{j1} < \alpha_{j2}$, to allow customers in the higher state to have higher purchase propensities as in Kumar et al. (2011). Indeed, based on the estimated state membership for the customers in the sample, the average contractual purchases are $58.82 for customers in the low state and $90.70 for customers in the high state. The average noncontractual purchases amount to $88.62 for customers in the low state and $167.59 for those in the high state.

Moreover, to assess the robustness and relative performance of the proposed model, it is compared to a benchmark bivariate Tobit model estimated through the conditional mixed process (CMP) procedure in Stata 14 software. The results of this model estimation are shown in Table 2. In contrast to the proposed model, this model assumes no unobserved heterogeneity and dynamics due to latent relationship states. The HMM model performs better than the benchmark model, in terms of both AIC and BIC. Furthermore, the corresponding sets of parameter estimates from the proposed and the benchmark model are consistent in direction and comparable in size, which indicates that the results of the former are quite robust.

The state-dependent purchases covariate estimates

Examining the parameter estimates presented in Table 3 reveals some interesting findings on the own- and cross-effects of relationship characteristics on the two purchase decisions.

Table 2: Benchmark Model Estimation Results

	Parameter	Estimate	Std. Error	t-value
Contractual	Intercept	-2.938	0.057	-51.69
	Contractual Cross-buying	2.494	0.117	21.38
	Contractual Tenure	0.000	0.000	6.55
	Contract Length	0.096	0.004	23.05
	Contractual Promotion usage	0.163	0.026	6.37
	Contractual Purchase frequency	0.203	0.109	1.87
	Contractual First purchase	-0.355	0.124	-2.87
	Noncontractual Cross-buying	0.283	0.060	4.71
	Noncontractual Tenure	0.000	0.000	-3.81
	Noncontractual Bundling	0.283	0.059	4.81
	Noncontractual Promotion usage	-0.017	0.055	-0.32
	Noncontractual Purchase frequency	-0.279	0.045	-6.26
	Noncontractual First purchase	-0.670	0.117	-5.75
Noncontractual	Intercept	-2.715	0.071	-38.08
	Noncontractual Cross-buying	2.130	0.060	35.26
	Noncontractual Tenure	0.001	0.000	8.30
	Noncontractual Bundling	2.563	0.065	39.38
	Noncontractual Promotion usage	-0.050	0.034	-1.47
	Noncontractual Purchase frequency	0.194	0.026	7.37
	Noncontractual First purchase	0.045	0.090	0.50
	Contractual Cross-buying	-0.758	0.282	-2.69
	Contractual Tenure	-0.001	0.000	-8.09
	Contract Length	-0.013	0.010	-1.30
	Contractual Promotion usage	-0.052	0.065	-0.79
	Contractual Purchase frequency	0.420	0.274	1.54
	Contractual First purchase	0.525	0.303	1.73
Covariance matrix	Std. Dev. Contractual	1.591	0.016	
	Std. Dev. Noncontractual	3.095	0.025	
	Corr. of Contractual and Noncontractual	0.114	0.013	
Log likelihood			-30,484	

Customers who engage in high contractual cross-buying tend to spend significantly and substantially more on contractual services ($\beta_{1,11}$=2.493, p-value<.01). This finding is intuitive and in line with prior research (e.g., Reinartz, Thomas, and Kumar 2005, Venkatesan and Kumar

2004) that has documented this positive own-effect. Those who engage in high noncontractual cross-buying tend to spend significantly more on both contractual ($\beta_{1,21}$=.228, p-value<.01) and noncontractual services ($\beta_{1,22}$=1.852, p-value<.01), although the own-effect (i.e., the effect of noncontractual cross-buying on noncontractual purchases) is substantially stronger that the cross-effect (i.e., the effect of noncontractual cross-buying on contractual purchases).

Customers who sign up for longer contracts spend significantly more on contractual purchases ($\beta_{3,11}$=.096, p-value<.01). Notably, customers who purchase larger product bundles spend significantly more on both types of services ($\beta_{3,21}$=.265, p-value<.01; $\beta_{3,22}$=1.566, p-value<.01). The own-effect is considerably stronger, but the existence of the cross-effect documents another way through which the two purchase behaviors influence each other.

Promotions appear to be significantly related to purchase propensities only when used on contractual services, as they are linked to increased contractual purchase amounts indicated by the own-effect of contractual promotion usage ($\beta_{4,11}$=.163, p-value<.01). No other promotion usage coefficients are found to be significant. Thus, consumers who use promotional deals on membership services tend to spend more on them, but not on noncontractual services. Moreover, usage of noncontractual promotional deals is not related to higher or lower purchase propensities for either type of purchase.

Customers tend to spend less on contractual services on the month of their first contractual purchase ($\beta_{6,11}$=-.341, p-value<.01), but they spend more on noncontractual services during that month ($\beta_{6,12}$=.603, p-value<.01). They also tend to spend less on contractual services on the month of their first noncontractual purchase ($\beta_{6,21}$=-.638, p-value<.01).

Interestingly, tenure has partially statistically significant but mostly negligible (close to zero) own- and cross-effects. This suggests that in this setting, customers' purchase propensities

Table 3: Proposed Hidden Markov Model Estimation Results

	Parameter	Estimate	Std. Error	t-value
Contractual	Intercept (low state)	-2.931	0.088	-33.213
	Additional intercept for high state	2.247	0.132	6.157
	Contractual Cross-buying	2.493	0.125	19.996
	Contractual Tenure	0.000	0.000	3.642
	Contract Length	0.096	0.018	5.366
	Contractual Promotion usage	0.163	0.031	5.245
	Contractual Purchase frequency	0.208	0.118	1.765
	Contractual First purchase	-0.341	0.122	-2.783
	Noncontractual Cross-buying	0.228	0.064	3.554
	Noncontractual Tenure	0.000	0.000	-0.612
	Noncontractual Bundling	0.265	0.076	3.462
	Noncontractual Promotion usage	-0.033	0.061	-0.546
	Noncontractual Purchase frequency	-0.249	0.042	-5.903
	Noncontractual First purchase	-0.638	0.115	-5.563
Noncontractual	Intercept (low state)	-1.906	0.049	-39.144
	Additional intercept for high state	19.990	0.020	149.370
	Noncontractual Cross-buying	1.852	0.053	34.919
	Noncontractual Tenure	0.000	0.000	8.660
	Noncontractual Bundling	1.566	0.045	34.726
	Noncontractual Promotion usage	0.014	0.029	0.482
	Noncontractual Purchase frequency	0.024	0.046	0.519
	Noncontractual First purchase	0.052	0.187	0.277
	Contractual Cross-buying	-0.290	0.209	-1.391
	Contractual Tenure	-0.001	0.000	-1.709
	Contract Length	0.008	0.011	0.708
	Contractual Promotion usage	-0.037	0.047	-0.795
	Contractual Purchase frequency	0.198	0.198	1.000
	Contractual First purchase	0.603	0.190	3.166
Transition matrix	Intercept (low to high)	-5.515	0.736	-7.493
	Intercept (high to high)	-1.115	2.321	-0.481
	Contractual Promotion usage (to high)	-0.902	0.417	-2.164
	Noncontractual Promotion usage (to high)	0.106	0.055	1.921
Covariance matrix	Std. Dev. Contractual	1.581	0.072	6.335
	Std. Dev. Noncontractual	1.883	0.119	5.330
	Corr. of Contractual and Noncontractual	0.115	0.014	105.674
Log likelihood			-28,067	

and the relevant spending levels do not differ significantly between older and newer customers for either contractual or noncontractual services, after controlling for the effects of the other relationship characteristics.

The transition matrix and covariance matrix estimates

Shifting focus to the transition matrix estimates reported in Table 3, the intercept for the probability of transition from the low to the high state ($\gamma_{low \rightarrow high}$=-5.515, p-value<.01) shows that the intrinsic value of this transition is significantly and substantially low for customers in the sample. This signals that the low state is "sticky", meaning that it is difficult for a customer with low relationship commitment to shift to high commitment. Additionally, the marginal effect of the two marketing-related covariates on transitioning to the high state varies. Specifically, contractual promotion usage is negatively related to the probability of moving to or staying at the high state ($\theta_{1,\rightarrow high}$=-.902, p-value<.05). This indicates that using contractual promotions is related to being in the low state. In contrast, noncontractual promotion usage is positively related to the probability of moving to or staying at the high state ($\theta_{2,\rightarrow high}$=.106, p-value<.05). Therefore, consumers who use promotional deals on noncontractual services are more likely to be in the high relationship commitment state. Finally, the covariance matrix shows that the two purchase behaviors are significantly and positively correlated (ρ_{12}=0.115, p-value<.01).

DISCUSSION

This study offers a framework of customers' purchasing behavior regardless of purchase setting. It is generalizable to other services with mixed contractual and non-contractual purchase elements – e.g., wireless providers' contractual and noncontractual accounts as well as add-on products (international calls, text packages, roaming, etc.). The inclusion of the CLV formula offers a tool for measuring the lifetime value of fitness customers and for identifying profitable customers when applied on a firm's customer base.

Overall, a variety of contractual and noncontractual purchase characteristics appear to have an influence on both purchase decisions. Noncontractual purchase characteristics are found to be more accurate predictors of contractual purchase propensities, as evidenced through a greater number of significant cross-effects. One set of notable findings pertains to cross-buying and bundling of noncontractual services being associated with higher purchase propensities for contractual services. Another interesting finding indicates that customers' contractual purchase propensity increases over their relationship with the firm, as their first such purchase tends manifest as lower purchase amounts in comparison. The findings on promotional usage also offer some interesting insights. On the short term, promotional deals on membership services are related to more customer spending on those services. On the long term, promotional deals on limited access services are related to a higher likelihood of customers being in the high relationship commitment state.

There are several implications of this study's findings for managerial practice. Customers with higher levels of cross-buying and bundling of standalone access services spend more on membership services, so incentivizing certain behaviors for one purchase type has the potential to influence customer choices relevant to the other purchase type. Contractual deals appear to have a short-term positive effect on the relevant customer spending, while noncontractual deals appear to have a long-term positive effect on relationship commitment. Managers should be aware of these relationships when designing sales promotions and plan them accordingly to achieve the desirable results. The overall findings suggest that marketers should differentiate between customers' contractual and noncontractual purchase behaviors – as some strategies work better for one vs. the other – but manage them together – the two purchase propensities are directly and indirectly related – and focus retention efforts on customers with purchase characteristics that drive customer purchase propensities and CLV.

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