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The Challenge of Retaining Customers Acquired with Free Trials

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The Challenge of Retaining Customers Acquired with Free Trials

ABSTRACT

Many service firms acquire customers by offering free-trial promotions. A crucial challenge is to retain customers acquired with these free trials. To address this challenge, firms need to understand how free-trial customers differ from regular customers in terms of their decision making to retain the service. This article conceptualizes how a customer's retention decision is driven by marketing communication and usage behavior, and develops hypotheses about the impact of free-trial acquisition on this process. To test the hypotheses, the authors model a customer's retention and usage decisions, distinguishing between usage of a flat-rate service and usage of a pay-per-use service. The model allows for unobserved heterogeneity and corrects for selection effects and endogeneity. Based on household panel data from a digital TV service, the authors find systematic behavioral differences which make the average customer lifetime value (CLV) of free-trial customers 59% lower than that of regular customers. However, free-trial customers are more responsive to marketing communication and usage rates, which offers opportunities to target marketing efforts and enhance retention rates, CLV, and customer equity.

KEYWORDS: Free Trials, Customer Retention, Usage Behavior, Customer Lifetime Value, Customer Equity, Acquisition Mode, Selection Effects, Endogeneity, Econometrics

A very popular way to acquire new customers, especially among service providers, is to offer free-trial promotions. Customers on a free trial are allowed to try the service for a limited amount of time at no charge. Well-known examples are the free trials offered by mobile telephone operators (e.g., AT&T in the US), video streaming websites (e.g., Netflix in the US), and digital TV providers (e.g., Sky television in Australia and New Zealand). While these free trials may be popular with consumers, a crucial challenge to firms is to retain customers who have been acquired with a free trial. To address this challenge, firms need to understand whether customers attracted with free trials are systematically different from other customers. In this article, we argue that free-trial acquisition may affect the nature of a customer's relationship with the service provider and, as a consequence, influence usage and retention behavior, consumers' responsiveness to marketing activities, and ultimately customer lifetime value (CLV).

An emerging body of research has shown that the conditions under which customers are acquired have implications for subsequent consumer behavior (e.g., Reinartz, Thomas, and Kumar 2005; Schweidel, Fader, and Bradlow 2008). A first group of studies documents the role of the sales channel through which customers have been attracted (e.g., Steffes, Murthi, and Rao 2011). For example, Verhoef and Donkers (2005) find that acquisition through the Internet leads to higher retention rates than acquisition through direct mail or direct-response commercials. A second set of papers addresses the impact of customer referral (Chan, Wu, and Xie 2011; Schmitt, Skiera, and Van den Bulte 2011). Villanueva, Yoo, and Hanssens (2008), for instance, show that customers acquired through word-of-mouth referral have longer lifetimes.

A third stream of research, in which we position our own work, examines the effects of the price structure or promotional conditions under which customers were acquired. Iyengar et al. (2011) find that customers of a telecommunication company who were acquired under a two-

part tariff structure have lower usage and retention rates than customers charged on a pay-per-use basis.¹ Lewis (2006) shows that acquisition discounts lead to lower retention rates, while Anderson and Simester's (2004) results indicate that promotionally acquired customers choose cheaper products but buy more. Table 1 summarizes the relevant research.

[PLEASE INSERT TABLE 1 ABOUT HERE]

This article contributes to the literature in three ways. First, while previous work has examined the impact of promotional customer acquisition on subsequent behavior, the effects of *free-trial* promotion have remained largely unaddressed. A free trial involves a distinct type of sales promotion which enables consumers to start using a service without a financial obligation and to revise their initial adoption decision if they are not satisfied. A free trial thus allows consumers to engage in a low-commitment relationship with the firm (Dwyer, Schurr, and Oh 1987). Relying on buyer-seller relationship theory, we will argue that this may lead to systematic differences in behavior between free-trial and regular customers.

Although some studies examine the effects of free trials and sampling, most look at *aggregate* sales (e.g., Heiman et al. 2001; Jain, Mahajan, and Muller 1995; Pauwels and Weiss 2008) or focus on *immediate* purchase effects (Scott 1976). Gedenk and Neslin (1999), who do study individual customer behavior, find that sampling in the mineral water category reinforces choice probabilities after the promotion. However, the authors do not examine retention, as this is not relevant for FMCGs. Bawa and Shoemaker (2004) show that free samples attract new buyers who may remain customers in subsequent periods. Yet, it is unclear whether the retention rates of customers attracted with a sample differ from those of regular customers.

As a second contribution, we extend insights on the role of *usage behavior* in the customer value generation process. Specifically, usage intensity can be an important driver of

retention because it reminds customers about the personal value of the service (e.g., Bolton and Lemon 1999; Prins, Verhoef, and Franses 2009). This paper adds to these insights by examining how free-trial acquisition influences the relationship between usage and retention. In particular, if this relationship turns out to be particularly strong for customers acquired via free trial, it is in the firm's interest to encourage usage especially among these customers. An important consideration in this respect is that many services involve two types of usage: flat-rate usage (e.g., a regular TV subscription) and pay-per-use consumption (e.g., video-on-demand). While both types of usage drive retention, usage of a pay-per-use service is also a *direct* source of revenues (e.g., Danaher 2002; Iyengar et al., 2011). Therefore, we distinguish between flat-rate and pay-per-use service components and examine the role of usage, not only as an antecedent of retention but also as a direct component of CLV.

Third, a crucial yet unexplored question is whether acquisition mode affects *customers'* *responsiveness* to the firm's marketing communication efforts. Therefore, we evaluate the differences in marketing responsiveness between free-trial and regular customers. Specifically, we consider customers' reaction to direct marketing and traditional advertising because of the growing interest in marketing communication as a way to actively manage customers' tenure (e.g., Polo, Sese, and Verhoef 2011; Reinartz, Thomas, and Kumar 2005). If free-trial and regular customers respond differently to direct marketing and advertising, firms may decide to target retention efforts to the most receptive group to reduce churn.

In sum, we investigate whether free-trial acquisition influences retention behavior and CLV, and how it moderates the extent to which retention is driven by service usage (flat-rate and pay-per-use) and marketing communication. We develop econometric models for customers' usage and retention decisions, accounting for unobserved heterogeneity and endogenous

marketing instruments. Importantly, because we are interested in the impact of free-trial acquisition on a customer's behavior, we correct for selection effects. In particular, free trials may attract consumers with, a priori, lower valuations of the service (e.g., Lewis 2006). While previous research on the role of acquisition mode typically ignores selection effects (see Table 1), we consider two alternative approaches to address these effects, i.e., explicit modeling of the selection process (e.g., Thomas 2001) and matching (e.g., Gensler, Leeflang, and Skiera 2012).

Based on household panel data for more than 16,000 customers of a large European digital TV provider, we find that free-trial customers have lower retention rates and use the firm's flat-rate service less intensively than regular customers. As a result, their CLV is, on average, 59% lower than that of regular customers. However, free-trial customers are more responsive to marketing communication and more likely to rely on their usage behavior when deciding whether or not to retain the service. These findings offer managers opportunities to better target their marketing efforts and improve retention rates, CLV, and customer equity.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

Figure 1 presents the conceptual framework for this research. The core consists of a customer's usage and retention decisions, which are influenced by the acquisition mode, i.e., free-trial versus regular acquisition.

[PLEASE INSERT FIGURE 1 ABOUT HERE]

Core Decision Process

The core decision process involves two types of periodic (e.g., monthly) decisions. Every period, consumers decide how intensively to use the service and whether to retain it or not.

Service usage. We distinguish between two types of service usage that are common for subscription services: (1) usage of a flat-rate service, which is included in the subscription

charges, and (2) usage of a pay-per-use service, for which consumers pay per unit of consumption. While both types of usage may foster retention, consumption of the pay-per-use service, in addition, directly generates revenue.

Service retention. Every period, consumers decide whether to retain the service or not. We distinguish between two sets of drivers for this decision. First, consumers rely on their usage intensity for the flat-rate and pay-per-use component to assess the utility of retaining the service (Bolton and Lemon 1999). As a result, a high usage intensity will stimulate retention, whereas a low usage rate may lead to disadoption (Lemon, White, and Winer 2002). Note that, compared to usage of the pay-per-use service, flat-rate usage may be more consequential for customers' evaluation of the service subscription, because it is included in the fixed periodical fee (Bolton and Lemon 1999). Second, a consumer's retention decision is also influenced by marketing communication (e.g., Blattberg, Malthouse, and Neslin 2009). Specifically, direct marketing and advertising remind customers of the benefits of the service or directly persuade them to retain it.

If consumers retain the service in the current period, they go through the same usage and retention decision process in the following period. As indicated by the dashed lines, this repeated decision process drives customer lifetime value (CLV). In particular, the periodic retention decisions generate a stream of fixed subscription fees (which cover flat-rate usage) while usage of the pay-per-use service generates additional revenue.

Differences between Free-Trial and Regular Customers

Central to our study is the expectation that the decision process to use and retain the service differs between free-trial and regular customers. Our hypotheses build on buyer-seller relationship theory, which posits that customer behavior depends on the nature of the relationship between customer and firm (Dwyer, Schurr, and Oh 1987; Johnson and Selnes 2004).

Baseline retention. Drawing on relationship theory, we expect free-trial customers to churn sooner than regular customers. Whereas the anticipated longevity of a *regular* contract encourages customers to immediately commit to the firm, subscription to a *free trial* resembles a discrete transaction which merely increases a consumer's awareness of the firm and facilitates relationship exploration (Dwyer, Schurr, and Oh 1987; Johnson and Selnes 2004). According to self-perception theory, free-trial customers may make post-hoc inferences about the reasons for their behavior and hence attribute their adoption decision to the availability of a free trial rather than to a strong commitment to the company (e.g., Dodson, Tybout, and Sternthal 1978; Gedenk and Neslin 1999). In other words, a free trial slows down the relationship formation process (Palmatier et al. 2013). Importantly, even after the free-trial period has expired, the firm's relationship with free-trial customers likely remains more fragile than that with regular customers. In particular, research by Gilbert and Ebert (2002) and Gilbert et al. (1998) indicates that consumers who receive the opportunity to first evaluate a product or service are more critical than when they immediately commit to the firm, a tendency that persists after the evaluation period. That is, the critical reflections generated during exploration of a relationship remain active, even when the customer moves to a closer relationship level. Hence, we hypothesize that:

- H₁ Free-trial customers have a lower retention rate than regular customers even after the free trial expires.

Impact of usage on retention. Because customers attracted with a free trial arguably have a less developed relationship with the firm than regular customers, they may be more uncertain about the service benefits (Johnson and Selnes 2004). One major factor that informs consumers about the personal value of the service and thus helps to resolve the uncertainty, is their own usage behavior (e.g., Bolton and Lemon 1999). A customer may wonder: Do I use the service

enough to stay subscribed? We expect that, to overcome their uncertainty, free-trial customers are more inclined than regular customers to assess the service's value on the basis of their flat-rate and pay-per-use consumption. Regular customers, who are more committed to the firm, are less likely to base their retention decision on usage intensity. Hence, we expect that:

H_{2a} The impact of usage of a flat-rate service on retention is greater for free-trial customers than for regular customers.

H_{2b} The impact of usage of a pay-per-use service on retention is greater for free-trial customers than for regular customers.

Impact of marketing communication on retention. We also argue that the firm's marketing communication, in the form of direct marketing and advertising, will be more important to free-trial than to regular customers. Marketing communication provides free-trial customers with information that can compensate for their relatively high uncertainty (Mitchell and Olson 1981). Regular customers, in contrast, may be less susceptible to external information because of confidence in their level of expertise (Brucks 1985; Hoch and Deighton 1989). In line with these principles, Johnson and Selnes (2004) postulate that it is easier to boost commitment among customers in a lower-level relationship with the firm than among already dedicated customers. As a result, we expect that free-trial customers are more responsive to the firm's direct-marketing and advertising efforts than regular customers:

H_{3a} The impact of direct marketing on retention is greater for free-trial customers than for regular customers.

H_{3b} The impact of advertising on retention is greater for free-trial customers than for regular customers.

Baseline usage. Free-trial acquisition may also affect customers' usage intensity. On the

one hand, free-trial customers are less committed to the firm and less convinced of the service benefits, such that they may have lower usage rates than regular customers. In fact, usage is one of the most tangible reflections of engagement with the firm (Van Doorn et al. 2010). This holds true in particular for usage of the *flat-rate service*, which is the main object of the contractual relationship (Bolton and Lemon 1999). On the other hand, exactly because free-trial customers' relationship with the firm is more exploratory in nature (Dwyer, Schurr, and Oh 1987; Gilbert et al. 1998), they may use the service more frequently to become more certain about the service's benefits. These opposing principles do not allow us to develop unidirectional expectations regarding the impact of free-trial acquisition on usage of the flat-rate and pay-per-use services.

DATA

Study Context

We test the hypotheses based on a household panel data set from a large European interactive TV (iTV) provider. iTV is a technology that enables customers to interact with their TV, for example, by browsing an electronic program guide or watching video-on-demand (VOD). Furthermore, iTV offers enhanced image quality over regular TV. To use the iTV service, customers need a broadband DSL Internet connection from the same company and a set-top box which decodes the digital signal. The focal company is the only provider of digital TV via DSL and, at the end of the observation period, had a market share of 31% in the digital TV market. Its main competitor, which offers digital TV via cable, had a market share of 40%.²

Under regular conditions, the company's customers formally commit to a 12-month subscription period. They have the possibility to cancel the service earlier, in which case they pay a penalty (€50, plus €6 for every remaining month until the end of the contractual period). After the first twelve months, the contract is automatically renewed but can be terminated each

month without penalty. Customers are charged a one-time setup fee for hardware and activation (on average €16.24) and pay for service usage according to a two-part tariff structure (e.g., Ascarza, Lambrecht, and Vilcassim 2012; Iyengar et al. 2011). Specifically, the fixed monthly subscription fee of €15.95 covers unlimited usage of the basic iTV service (€9.95) and rent of the set-top box (€6). Additionally, customers can make use of a video-on-demand (VOD) service, for which they are charged on a pay-per-use basis. They can select VODs from an electronic catalogue containing movies, live concerts, and soccer games. VOD rental for 24 hours costs around €3, with some limited variation in price due to differences in genre and length.

The company's acquisition strategy offers a unique setting to study the impact of free-trial acquisition. For a period of 10 months (months 10 till 19 after launch of the service), the company offered free trials parallel to its regular subscriptions. Adoption of the free trial (as opposed to the regular subscription) is largely driven by consumers' awareness of the ongoing free-trial promotion, which was mainly promoted via direct marketing. Customers acquired with a free trial did not pay setup costs and were not charged monthly subscription fees for the usage of the flat-rate service during a three-month period. VOD usage, however, was not free of charge. Free-trial customers could revise their adoption decision by returning the set-top box to one of the company stores before the end of the trial period, without paying a penalty. If the product was not returned by the end of the three-month trial period, the subscription was converted into a paid one, such that the next nine months were considered part of a regular contract.

Data set

From the initial sample of close to 21,000 customers who adopted iTV when both the free trial and regular subscription were available, we retain a subset based on several criteria.

Specifically, we eliminate customers who had missing socio-demographics, were employees of the focal company, or did not speak the local language (and thus could not understand the advertising and direct-marketing messages). We thus retain 16,512 customers of which 12,612 (76%) were acquired with free trials and the balance of 3,900 (24%) signed a regular contract.

We observe customers' retention and usage behavior until two years after launch of the service. 6,079 (48%) of the free-trial customers churn before the end of the observation period, while of the regular customers only 1,327 (34%) do so. Furthermore, the data set includes two types of usage: (1) flat-rate usage of the basic interactive TV service, which is measured by a customer's monthly number of channel zaps,³ and (2) usage of the VOD service, for which we use the monthly number of VODs the customer has watched. Compared to regular customers, free-trial customers have an average usage intensity that is 11% lower for the flat-rate service (169 versus 189 zaps per month), but 26% higher for the video-on-demand service (.73 versus .58 VODs per month). However, these retention and usage measures are only indicative, because they do not account for selection effects or the impact of marketing activities.

The company uses two types of marketing communication: direct marketing and mass advertising. We operationalize direct marketing as the monthly number of direct-marketing contacts with a given customer (via phone, e-mail, or regular mail). On average, free-trial and regular customers are contacted .34 and .16 times per month, respectively. In the analyses, we account for these systematic differences in contact frequency. In addition, the data set includes a measure for the company's spending on mass advertising (via TV, print media, radio, and the Internet). In particular, this variable quantifies the company's advertising expenditures for a given region in a given month, relative to the total advertising spending for the same region and month by the company and its main competitor. This share-of-voice advertising measure varies

between 0 and 1, and has an average of .74 for free-trial and .79 for regular customers. Table 2 lists summary statistics of the variables in the data set, while Web Appendix A reports the correlations between the independent variables. We give more details on the control variables and socio-demographic variables when we discuss the model.

[PLEASE INSERT TABLE 2 ABOUT HERE]

MODEL

We specify a set of equations that incorporates the interrelationships between customers' usage (flat-rate and pay-per-use) and retention decisions. We account for unobserved customer heterogeneity, the endogeneity of marketing communication, and selection effects.

Retention

The probability of retention is modeled with a binomial Probit model. Each customer i decides at the end of every month t after acquisition whether to retain the service ($r_{it} = 1$) or disadopt ($r_{it} = 0$). We write the utility v_{it} of retaining the service as follows:

$$(1) \quad v_{it} = \alpha_{0i} + \alpha_{1i}\text{Trial}_i + \alpha_{2i}\text{UsageFR}_{it} + \alpha_{3i}\text{UsagePPU}_{it} + \alpha_{4i}\text{DM}_{it} + \alpha_{5i}\text{Adv}_{it} + \\ \alpha_{6i}\text{UsageFR}_{it} \times \text{Trial}_i + \alpha_{7i}\text{UsagePPU}_{it} \times \text{Trial}_i + \alpha_{8i}\text{DM}_{it} \times \text{Trial}_i + \alpha_{9i}\text{Adv}_{it} \times \text{Trial}_i + \\ \alpha_{10,i}\text{Initial}_{it} + \alpha_{11,i}\text{Fee}_{it}^{\text{sub}} + \alpha_{12,i}\text{Penalty}_{it} + \alpha_{13,i}\text{Temp}_{it} + \alpha_{14,i} \log(\text{Time}_{it}) + \xi_{it}$$

Thus, the utility of retaining the service at the end of month t is influenced by the dummy Trial_i (1 if customer i was acquired with a free-trial; 0 otherwise). This allows us to test whether free-trial acquisition increases a customer's churn rate (H_1). Other drivers include the customer's usage of the flat-rate (UsageFR_{it} , measured in monthly channel zaps divided by 100) and pay-per-use services (UsagePPU_{it} , measured in number of VODs) in month t . Retention also depends on the company's monthly direct-marketing efforts (DM_{it} , the number of direct-marketing

contacts received by customer i) and advertising intensity (Adv_{it} , the company's share-of-voice in customer i 's region).⁴ Equation 1 also includes the interactions between $Trial_i$ and the usage and marketing-communication variables to test $H_{2a,b}$ and $H_{3a,b}$, which posit that the impact of usage and marketing communication is stronger for free-trial than for regular customers.

Finally, the equation includes a set of control variables. The model accounts for a general pattern of high defection rates during the first four months of a customer's tenure through the dummy variable $Initial_{it}$. The subscription fee for customer i in month t , Fee_{it}^{sub} , captures the influence of price on a customer's retention decision (Ascarza, Lambrecht, and Vilcassim 2012). Variation in Fee_{it}^{sub} is due to temporary price reductions and the zero-price in the beginning of a free-trial customer's tenure. Moreover, we include the variable $Penalty_{it}$ to account for the fact that customers were able to cancel their 12-month subscription by paying an early-termination fee. We assume that customers trade off the termination fee against future subscription fees within the current contractual period. Hence, $Penalty_{it}$ equals the termination fee for immediate disadoption minus the sum of all future subscription fees that the customer would have to pay during the remaining months of the contractual period. The higher $Penalty_{it}$, the more likely it is that the customer retains the service.

Importantly, the variables Fee_{it}^{sub} and $Penalty_{it}$ control for the systematically higher defection rates of free-trial customers, compared to regular customers during the free-trial period. In this period, free-trial customers face zero subscription and cancelation fees compared to *nonzero* subscription and cancelation fees for regular customers. Hence these control variables allow us to obtain a clean test of H_1 via the trial dummy in Equation 1, which equals one for a free-trial customer even after the free-trial period is over.

We include the monthly average temperature ($Temperature_{it}$) to control for seasonality,⁵

and the log of time-since-adoption (Time_{it}) to accommodate fluctuations in the baseline retention probability (Prins, Verhoef, and Franses 2009). The model coefficients $\alpha_{0i}, \dots, \alpha_{14,i}$ are customer-specific and normally distributed. Finally, the Probit error term ξ_{it} is normally distributed with a standard deviation set equal to 1 for identification purposes.

Usage of the Flat-Rate Service

We model flat-rate usage (UsageFR_{it}) as a log-log regression to account for the skewed nature of this variable (Iyengar et al. 2011):

$$(2) \quad \log(\text{UsageFR}_{it}+1) = \beta_{0i} + \beta_{1i}\text{Trial}_i + \beta_{2i}\log(\text{UsageFR}_{i,t-1}+1) + \beta_{3i}\log(\text{Fee}_{it}^{\text{sub}}+1) + \\ \beta_{4i}\log(\text{Temp}_{it}) + \beta_{5i}\log(\text{Time}_{it}) + \theta_{it}$$

The free-trial acquisition dummy Trial_i captures differences in flat-rate usage between free-trial and regular customers. The lagged dependent variable $\text{UsageFR}_{i,t-1}$ accounts for persistence in usage behavior. We also include the control variables subscription fee, average temperature, and time-since-adoption.⁶ Before taking the logarithm, we add 1 to all variables for which zeros occur (e.g., Iyengar et al. 2011). $\beta_{0i}, \dots, \beta_{5i}$ are normally distributed customer-specific coefficients and θ_{it} is an error term following a normal distribution, $N(0, \sigma^2)$.

Usage of the Pay-per-Use Service

We model usage of the pay-per-use component, i.e., a consumer's monthly number of VODs, with a zero-inflated Poisson model, in which the zero inflation accommodates the spike at zero in the VOD usage variable:

$$(3) \quad \text{UsagePPU}_{it} = \text{UsagePPU}_{it}^* \sim \text{Poisson}(\lambda_{it}) \quad \text{with probability } q_i \\ \text{UsagePPU}_{it} = 0 \quad \text{with probability } 1 - q_i$$

where q_i is the probability that customer i is a potential user of the VOD service, modeled with a Probit structure with customer-specific normally distributed intercept; UsagePPU_{it}^* is the number

of VODs watched by customer i in period t , given that the customer is a potential VOD user. The expected number of VODs, λ_{it} , is specified as an exponential function to ensure a positive sign:

$$(4) \quad \lambda_{it} = \exp(\gamma_{0i} + \gamma_{1i}\text{Trial}_i + \gamma_{2i}\text{UsagePPU}_{i,t-1} + \gamma_{3i}\text{Fee}_{it}^{\text{sub}} + \gamma_{4i}\text{Temp}_{it} + \gamma_{5i}\log(\text{Time}_{it}) + \gamma_{6i}\text{Credit}_{it}).$$

Similar to the model for flat-rate usage, the expected number of videos watched is a function of acquisition mode (Trial_i), a customer's past usage ($\text{UsagePPU}_{i,t-1}$), and the variables $\text{Fee}_{it}^{\text{sub}}$, Temp_{it} , and $\log(\text{Time}_{it})$. Credit_{it} is the VOD credit for customer i in month t (measured in €). This VOD credit is granted by the company for a maximum period of four months to stimulate service usage. $\gamma_{0i}, \dots, \gamma_{6i}$ are normally distributed customer-specific coefficients.

Customer Heterogeneity

We include customer heterogeneity by modeling all response parameters (intercepts and slope coefficients) as normally distributed across customers. To incorporate interdependence between the different model components, we allow for correlations between the intercepts.⁷ The expected values of the retention and usage intercepts α_{0i} , β_{0i} , and γ_{0i} are functions of the concomitant customer characteristics age, household size, income (e.g., Rust and Verhoef 2005), and time-to-adoption (Prins, Verhoef, and Franses 2009; Schweidel, Fader, and Bradlow 2008):

$$(5) \quad \begin{pmatrix} E(\alpha_{0i}) \\ E(\beta_{0i}) \\ E(\gamma_{0i}) \end{pmatrix} = \begin{pmatrix} \alpha_{0,0} + \alpha_{0,1}\text{Age}_i + \alpha_{0,2}\text{Hhsize}_i + \alpha_{0,3}\text{Income}_i + \alpha_{0,4}\text{Adopttime}_i \\ \beta_{0,0} + \beta_{0,1}\text{Age}_i + \beta_{0,2}\text{Hhsize}_i + \beta_{0,3}\text{Income}_i + \beta_{0,4}\text{Adopttime}_i \\ \gamma_{0,0} + \gamma_{0,1}\text{Age}_i + \gamma_{0,2}\text{Hhsize}_i + \gamma_{0,3}\text{Income}_i + \gamma_{0,4}\text{Adopttime}_i \end{pmatrix}$$

where Age_i is the age of customer i (in years, shortly after service launch), Hhsize_i is the size of customer i 's household (in number of persons), Income_i is the average income in the census block to which customer i belongs (in €10,000), and Adopttime_i is the time-to-adoption of customer i (measured in months following the launch of the iTV service).

Correction for Endogeneity of Marketing Instruments

Endogeneity due to temporal correlation. The first type of endogeneity that we address involves temporal correlation of DM_{it} and Adv_{it} with the error term of the retention equation. For example, the company may counteract expected increases in the churn rate by boosting its marketing efforts. Following Park and Gupta (2012) and Schweidel and Knox (2013), we use Gaussian copulas to model the correlation between marketing and the error term. While classical methods to correct for endogeneity rely on instrumental variables (IVs) to partial out the exogenous variation in the endogenous regressors, copulas do not require IVs (Park and Gupta 2012; Schweidel and Knox 2013). In line with Park and Gupta (2012, p. 573), we add the following regressors to Equation 1:

$$(6) \quad \begin{aligned} \widetilde{DM}_{it} &= \Phi^{-1}(H_{DM}(DM_{it})) \text{ and} \\ \widetilde{Adv}_{it} &= \Phi^{-1}(H_{Adv}(Adv_{it})), \end{aligned}$$

where Φ^{-1} is the inverse of the normal cumulative distribution function and $H_{DM}(\cdot)$ and $H_{Adv}(\cdot)$ represent the empirical cumulative distribution functions of direct marketing and advertising, respectively.⁸ For identification purposes, the endogenous regressors must be non-normally distributed (Park and Gupta 2012), which a Shapiro-Wilk test shows to be the case (direct marketing: $W = .8255, p < .001$; advertising: $W = .7948, p < .001$).

Endogeneity due to cross-sectional correlation. Second, endogeneity may arise from cross-sectional correlation of the marketing activities with the random intercept. Specifically, the company may target its direct-marketing efforts on the basis of consumer characteristics (unobserved to the researcher) that correlate with customers' churn rates. To address this type of endogeneity, we follow Mundlak (1978) and include the average number of direct-marketing contacts per customer, $\overline{DM}_i$, as a covariate in Equation 1 (e.g., Risselada, Verhoef, and Bijmolt

2014). Because the focal firm uses advertising as a mass-communication device, Adv_{it} is not subject to this type of endogeneity. In the estimation, we assess the added value of the Mundlak correction for cross-sectional endogeneity, on top of the correction for temporal endogeneity.⁹

Correction for Selection

Selection model. We use two alternative approaches to correct for selection effects: a selection model and matching. The selection model approach estimates the retention and usage models jointly with an additional model for consumers' selection into the free-trial or regular customer group. By allowing for correlation between the error of the selection equation and the random intercepts of the usage and retention models, we account for selection effects due to unobserved variables (Thomas 2001). Since the selection is a single event (sign up as a free-trial or regular customer), we need to allow for correlations with the random intercepts in retention and usage rather than with the time-varying error terms. To model whether a customer was acquired with a free-trial ($Trial_i = 1$) or not ($Trial_i = 0$), we use a binary probit structure and write the underlying utility of free-trial acquisition as follows:

$$(7) \quad w_i = \omega_0 + \omega_1 Age_i + \omega_2 Hsize_i + \omega_3 Income_i + \omega_4 Adopttime_i + \omega_5 DM_i^* + \omega_6 Adv_i^* + \omega_7 Fee_i^* + \zeta_i$$

The drivers include age, household size, income, time-to-adoption, and three marketing variables. DM_i^* represents the average number of direct-marketing contacts received by customer i in the three months before signing up. Because the free trial was often promoted in direct-marketing contacts (e.g., in outbound telephone calls), DM_i^* likely has a positive impact on consumers' awareness of the trial offer. Adv_i^* is the average share-of-voice for customer i in the three months before signing up. Because advertising usually promoted the regular offer, we expect Adv_i^* to decrease the probability that a customer was acquired through a free trial. Fee_i^*

refers to the total fees for a regular 12-month subscription at the time of customer i 's signup. Higher fees for the regular subscription may lead consumers to search longer for a special deal or push harder when in touch with a customer service agent, such that Fee_i^* should have a positive effect on the probability of free-trial acquisition. Finally, ζ_i is a standard-normal error term.

Matching procedure. As an alternative to jointly estimating the selection, retention, and usage models, we apply a matching procedure which pairs free-trial customers with the most comparable regular customers. We estimate the models on this matched data set such that differences in retention and usage behavior can be attributed to the acquisition mode rather than to differences in sample composition (Gensler, Leeflang, and Skiera 2013; Gensler, Leeflang, and Skiera 2012). To match subjects, we first estimate Equation 7 to compute customers' propensities of adopting the service on a free trial. Following Gensler, Leeflang, and Skiera (2013), we apply a hybrid procedure which combines subjects not only on the basis of their propensity scores but also on the basis of drivers of the selection process, i.e., the variables DM_i^* , Adv_i^* , and Fee_i^* . Next, we compute the Mahalanobis distances among consumers on the basis of their propensity scores and these three variables.¹⁰ Finally, we use the one-nearest neighbor algorithm to identify 12,610 pairs of free-trial customers and their most comparable regular customers (Gensler, Leeflang, and Skiera 2012).

EMPIRICAL RESULTS

We use simulated maximum likelihood with Halton draws to calibrate the usage and retention models. Before discussing parameter estimates, we check model performance and the robustness of the results across alternative approaches to tackling endogeneity and selection. We then evaluate model fit for the selected approach in detail and discuss the estimation results.

Robustness Checks and Model Selection

We compare two ways to correct for marketing endogeneity – copula and Mundlak terms versus a more parsimonious approach with just the copula terms – and two ways to address selection effects – the selection model versus matching. We discuss model performance and the robustness of the results across all four combinations. To assess model performance, we evaluate the retention model's in-sample fit and out-of-sample fit (cross-sectional and longitudinal) on three fit measures: hit probability (Gilbride, Allenby, and Brazell 2006), top-decile lift, and Gini coefficient (Lemmens and Croux 2006). While in- and out-of-sample fit are not suited to compare models with and without endogeneity correction, they can be used to validate different approaches that all correct for endogeneity (Ebbes, Papies, and Van Heerde 2011). Table 3 shows that model M1 based on matched samples and including both copula and Mundlak terms outperforms the other models for seven out of nine fit criteria. Therefore, the rest of our discussion focuses on model M1. Notice, however, that the four models yield very comparable outcomes for the hypotheses tests, underlining the robustness of the results.

[PLEASE INSERT TABLES 3-5 ABOUT HERE]

Estimation Results

Table 4 reports in-sample and out-of-sample fit measures for the selected model M1 in more detail. In addition to the measures for the retention model, we use the correlation between actual and predicted values as a fit measure for usage of the flat-rate and pay-per-use services. Overall, the different measures suggest a good in- and out-of-sample model fit, for both free-trial and regular customers. The fit of the auxiliary propensity model (Equation 7) is adequate (hit probability: 66.71%) and the parameter estimates, reported in Web Appendix B, are face-valid.

Table 5 presents the parameter estimates for the focal models. For the heterogeneous

parameters, we focus on the population means. We first discuss the relationships of the conceptual framework and then address the effects of the control variables. Hypothesis tests are one-sided while the remaining tests are two-sided.

Core decision process. The results confirm the expectations for the core retention decision process. Retention is positively affected by flat-rate usage and usage of the pay-per-use service ($\alpha_2 = .728, p < .001$ and $\alpha_3 = .039, p < .001$, respectively). Usage drives retention because to the consumer it is an indication of the personal value of the service (e.g., Lemon, White, and Winer 2002). The impact of both direct marketing ($\alpha_4 = 1.565, p < .001$) and advertising ($\alpha_5 = .310, p < .001$) on retention is positive, which is consistent with earlier findings that marketing communication creates interest in the service and increases retention (e.g., Polo, Sese, and Verhoef 2011). The significant coefficients of the copula and Mundlak terms suggest that correcting for marketing endogeneity is indeed required ($\alpha_{15} = -.596, p < .001$; $\alpha_{16} = -.017, p < .001$, $\alpha_{17} = -2.111, p < .001$).

Differences between free-trial and regular customers. In support of H_1 , acquisition via free trials has a direct negative impact on retention ($\alpha_1 = -.278, p < .001$), even after controlling for higher churn during the free-trial period.¹¹ This is in line with the expectation that free-trial customers are less confident about retaining the service, because they are in a tentative relationship with the firm and are likely to attribute their subscription to extrinsic incentives (i.e., the trial), resulting in lower commitment (Dwyer, Schurr, and Oh 1987).

The positive interaction between the free-trial dummy and usage variables indicates that the usage effects are stronger for free-trial than for regular customers, which confirms H_{2a} and H_{2b} ($\alpha_6 = .040, p < .001$ for the flat-rate service and $\alpha_7 = .013, p < .001$ for the pay-per-use service). This is in line with the notion that free-trial customers, because of their lower

commitment, are more uncertain about the service's benefits and therefore rely more on their usage behavior when making retention decisions (Bolton and Lemon 1999).

In support of H_{3a} and H_{3b} , free-trial customers are more responsive to marketing communication instruments than regular customers ($\alpha_8 = .133, p < .001$ for direct marketing and $\alpha_9 = .154, p < .001$ for advertising). Similar to usage, advertising and direct marketing provide free-trial customers with cues that make them more secure about the service's value and assist them in their retention decision (Mitchell and Olson 1981).¹²

Free-trial customers use the flat-rate service less intensively than regular customers ($\beta_1 = -.269, p < .001$). This is in line with the notion that free-trial customers are less committed to the service's benefits. Interestingly, however, they use the pay-per-use service *more* intensively than regular customers ($\gamma_1 = .113, p < .001$). Because free-trial customers make less use of the flat-rate service, they may dedicate more time to exploring the paid add-on service (Schary 1971). In addition, they may perceive the free trial as a windfall gain, enticing them to spend more on the pay-per-use service (e.g., Heilman, Nakamoto, and Rao 2002).

Figure 2 shows plots of the average predicted and observed values for retention (Panel a), flat-rate usage (Panel b), and usage of the pay-per-use service (Panel c). The plots show that the model fits the retention and usage data well for both free-trial and regular customers. In Panel a, the predicted retention rates after the trial look very similar for free-trial and regular customers. However, the model unveils that these predicted retention rates are obtained in a very different way for these two customer groups. For free-trial customers, the baseline retention rate is lower, because the main effect of $Trial_i$ on retention utility is $\hat{\alpha}_1 = -.278$. However, this lower baseline rate is compensated by free-trial customers' stronger marketing responsiveness (see Table 5) and by the higher levels of direct marketing they received (see Table 2).

[PLEASE INSERT FIGURE 2 ABOUT HERE]

Control variables. The control variables have significant and face-valid effects. TV usage drops in warmer months for obvious reasons, and the VOD credit increases usage of the VOD service. In addition, we find positive carry-over effects for both usage components (e.g., Bolton and Lemon 1999).¹³ Higher subscription fees reduce a customer's probability to retain and use the service (e.g., higher fees reduce customers' budget and, as a result, decrease their paid VOD consumption). The concomitant consumer characteristics also play a significant role. For example, all else equal, larger families are likely to use the service more intensively (both the flat-rate and pay-per-use component). Finally, the table in Web Appendix C indicates that there are significant correlations between the random intercepts of the retention and usage equations.

IMPLICATIONS FOR CUSTOMER LIFETIME VALUE AND CUSTOMER EQUITY

To examine how the estimated effects influence CLV, we compare the CLV of free-trial and regular customers, and compute the elasticities of CLV with respect to changes in marketing communication efforts and customers' usage intensities. Throughout the calculations, we use customer-specific posterior parameter distributions (Train 2009).

For maximum comparability between free-trial and regular customers, we use the same global means for the marketing variables. Furthermore, to avoid comparing the behavior of (relatively tentative) free-trial customers in their first three months with (relatively confident) regular customers, we only analyze those customers who survived the first three months, retaining 8,624 free-trial customers and 3,145 regular customers. On top of that, in the simulations, we shock marketing or usage in the first month *after the trial period* (i.e., in month 4 of a customer's tenure). We now explain how we derive CLV from customers' retention and usage behavior.

Calculating Net CLV

We simulate customers' usage and retention behavior over a three-year time horizon. Previous research on other high-tech products and services uses the same simulation horizon, arguing that most of a customer's value is typically captured during these first three years (Kumar et al. 2008; Rust, Kumar, and Venkatesan 2011). We compute Net CLV as the total revenue stemming from a customer's consecutive retention and usage decisions minus the costs to acquire and retain that customer. For a given month, revenue consists of the fixed subscription fee and the pay-per-use fees for watching VODs (corrected for content costs) if the customer retains the iTV service, or the early-termination fee if the customer disadopts. On the cost side, we distinguish between direct-marketing and advertising expenditures to acquire and retain the customer. Other costs are not directly related to the number of customers or their usage intensity (e.g., the network infrastructure is owned by the company), and can thus be ignored in the computation of Net CLV. To compute the present value of future cash flows, we use an annual discount rate of 8.5%, which is common in this industry (e.g., Cusick et al. 2014).¹⁴ Web Appendix D provides the equations for the Net CLV calculations.

Survival times. As a first step towards calculating Net CLV, we investigate customers' expected survival times during the three-year simulation period. Figure 3 shows that free-trial customers churn much earlier than regular customers. The survival times are also characterized by considerable consumer heterogeneity, especially for free-trial customers. Thus, we can expect substantial differences in Net CLV between but also within the two customer groups.

[PLEASE INSERT FIGURES 3-6 ABOUT HERE]

Net CLV for free-trial and regular customers. The Net CLV results are shown in Figure 4. Panel a presents average revenues, costs, and the resulting CLV for both groups. The major

part of revenues comes from subscription fees. The pay-per-use service accounts for 13% (€36.82) of the total revenues from free-trial customers and 10% (€41.25) of the total revenues from regular customers. Regular customers, who cannot cancel the service for free during a trial period, pay a higher expected cancellation fee than free-trial customers (€16.19 versus €7.11). The costs for acquisition (€170.29 for free-trial and €169.89 for regular customers) and retention (€10.79 for free-trial and €14.01 for regular customers) are very comparable. After taking into account all revenues and costs, the resulting Net CLV is on average 59% lower for free-trial customers than for regular customers (€101.25 versus €244.62).

Panel b shows that there is considerable heterogeneity in Net CLV also *within* the free-trial and regular customer groups. Although free-trial customers, on average, have a lower Net CLV, several of them generate a relatively high value, as becomes clear from the substantial overlap between the two distributions.

Marketing communication and usage elasticities. The parameter estimates suggest that free-trial customers are significantly more responsive to changes in marketing communication and usage levels than regular customers. To quantify whether these differences are also managerially relevant, we calculate elasticities of Net CLV with respect to marketing communication and usage. We find these elasticities to be substantially higher for free-trial customers than for regular customers. As shown in Figure 5, panels a and b, the average advertising and direct-marketing elasticities of free-trial customers are .26 and .41, respectively. For regular customers, however, we find average elasticities of only .02 and .08, respectively.¹⁵

In a similar vein, we assess the extent to which Net CLV changes in response to an increase in usage (see Figure 5, panels c and d). For example, the iTV company could enhance usage by offering access to more channels (flat-rate service) or extending their VOD catalogue

(pay-per-use service). We find that the average flat-rate usage elasticity equals .75 for free-trial customers but only .17 for regular customers. Likewise, the average pay-per-use elasticity is .04 for free-trial customers, yet only .02 for regular customers.

Should a Company offer Free Trials?

One major finding of this research is that the expected value of customers attracted with free trials is less than the expected value of regular customers ($E(\text{CLV}_{\text{free-trial}}) = \text{€}101.25$ versus $E(\text{CLV}_{\text{regular}}) = \text{€}244.62$). Consequently, companies may wonder whether offering free trials is worth the effort. For a free trial to be beneficial, it should attract enough lower-value customers to at least keep the aggregated CLV, or “customer equity” (CE), constant. But how many customers does the free-trial need to attract?

To obtain an indication of the necessary number of additional customers, we can use the results of the CLV calculations. According to the estimates, the 8,624 free-trial customers who survive the free-trial period generate a total expected CE of €873,180 ($8,624 \times E(\text{CLV}_{\text{free-trial}})$). To generate the same equity *without* the free trial, the firm would have had to attract only 3,570 regular customers because $3,570 \times E(\text{CLV}_{\text{regular}}) = 8,624 \times E(\text{CLV}_{\text{free-trial}}) = \text{€}873,180$. Hence, offering consumers a free trial rather than a regular contract should lead to $\kappa = 8,624/3,570 = E(\text{CLV}_{\text{regular}})/E(\text{CLV}_{\text{free-trial}}) = 2.42$ times more customers to keep CE constant. If a company believes a free trial is able to attract more new customers than this threshold, we recommend offering the free trial rather than the regular contract because the expected expansion of the customer base will compensate for the customers’ lower CLVs; otherwise the company should not offer the trial.

Importantly, κ is not a fixed number but depends, to some extent, on the company’s marketing efforts. Specifically, the company can lower the threshold by increasing its marketing

efforts after acquisition, making it easier for the free trial to break even in terms of CE. Indeed, the results indicate that higher marketing efforts lead to a smaller difference between $E(\text{CLV}_{\text{free-trial}})$ and $E(\text{CLV}_{\text{regular}})$, such that the threshold $\kappa = E(\text{CLV}_{\text{regular}}) / E(\text{CLV}_{\text{free-trial}})$ decreases. We illustrate this principle in Figure 6. For example, for direct-marketing (versus advertising) efforts 20% above the observed average, κ drops from 2.42 to 2.26 (versus 2.36). Thus, with increased direct-marketing (advertising) expenditures, it suffices if the trial is only 2.26 (2.36) more successful at attracting customers than the regular offer. These insights help companies to trade off acquisition and retention efforts (e.g., Reinartz, Thomas, and Kumar 2005). For example, a company may decide to boost retention expenditures when a trial's acquisition targets are not met. Vice versa, a well-designed free-trial promotion may lead to a higher-than-expected increase in customers, which may justify lower retention efforts afterwards.

[PLEASE INSERT FIGURE 6 AND TABLE 6 ABOUT HERE]

Improving Retention and Customer Equity after Acquisition

When a company has acquired customers with free trials and regular subscriptions, a key managerial question is how to improve consumers' retention behavior and customer equity. Because free-trial customers are worth less than regular customers, some managers may decide to invest less in free-trial customers. However, their higher responsiveness to marketing communication actually suggests otherwise. Therefore, we recommend managers to pay specific attention to free-trial customers. To illustrate this recommendation, we simulate the impact on retention and CE of alternative targeting strategies after customer acquisition (see Table 6).

Suppose a manager has an additional monthly direct-marketing budget that enables her to increase direct-marketing efforts by €0.5 per customer for 20% of the customers. Given the company's total customer base of 160,000 customers at the end of the observation period, this

corresponds to a substantial marketing investment of about €576,000 ($160,000 \times 20\% \times €0.5 \times 36$ months). The question then becomes how to select the 20% target customers. Using the customers in the simulation data set, we consider different scenarios. In scenario 1, the manager simply selects customers from the company's database *by chance*, yielding an increase in retention (158.0%) and Net CE (115.9%) for the 20% targeted customers. The impact across the entire customer base is also substantial: 31.6% for retention, 23.0% for Net CE.

Alternatively, bearing in mind our finding that acquisition mode influences customers' response to marketing communication, a manager could follow scenario 2 and target a random subset of *free-trial* customers. Such a strategy would improve retention and Net CE of the selected customers even more (186.7% for retention and 136.0% for Net CE). These returns stand in sharp contrast to scenario 3 in which the manager invests only in a random selection of *regular* customers, leading to an increase of 95.6% for retention and 75.6% for Net CE. Finally, a manager could opt for scenario 4 in which individual-level response coefficients are used to select customers with the highest responsiveness to direct-marketing. Such an optimal strategy would improve retention and Net CLV by 181.4% and 132.9% for targeted customers, and 36.3% and 26.6% for all customers. Notice that targeting free-trial customers (scenario 2) leads to results that come close to the optimal ones.

DISCUSSION

Recent research suggests that the way in which customers are acquired may have an enduring impact on their behavior, even long after adoption (e.g., Villanueva, Yoo, and Hanssens 2008). While some studies have found differences between customers attracted with sales promotions and regular customers (Anderson and Simester 2004; Lewis 2006), the challenge of retaining customers acquired through free-trial promotions is not well understood. Crucial

questions have remained unanswered: How do free-trial customers differ from regular customers in their retention rates, marketing responsiveness, and lifetime value? Should free-trial customers be managed in a different way?

To answer these questions, we model a customer's decisions to use and retain the service – decisions that influence CLV – and examine how free-trial acquisition affects this decision process. We explicitly account for selection effects (i.e., customers attracted with free trials may differ intrinsically from other customers) and for the endogeneity of marketing communication. The model is estimated on a unique panel data set, covering monthly usage (of flat-rate and pay-per-use services) and retention decisions for 16,512 customers of an interactive digital TV service provider. We then use the parameter estimates to simulate CLV and quantify its sensitivity to changes in marketing communication and usage rates.

Throughout the analyses, we find strong evidence for systematic differences in behavior between free-trial and regular customers. In line with buyer-seller relationship theory, which suggests that free trials may slow down the relationship formation process, free-trial promotions are associated with higher defection rates, even beyond the free-trial period. Similarly, flat-rate usage – an important driver of customers' retention decisions – turns out to be lower among free-trial subscribers. Interestingly, however, free-trial customers have a higher pay-per-use consumption rate. Apparently, they readily reallocate the time they gain (due to their lower flat-rate consumption) and the money they save (due to the free trial) to the pay-per-use service. These results add to the growing understanding of the role of usage in the value generation process (e.g., Bolton and Lemon 1999; Iyengar et al. 2011).

Managerial Implications

Our study has a number of key managerial implications. Because of their higher churn

rate, free-trial customers are worth considerably less than regular customers. Specifically, we find the Net CLV of free-trial customers to be 59% lower than that of regular customers. Managers and business analysts may thus have to temper profit expectations if the customer base includes a substantial share of free-trial subscribers. At the same time, we find free-trial customers to be more “malleable” than regular customers. Because they have a less-developed relationship with the firm, free-trial customers are more uncertain about the service benefits. As a result, they rely more on marketing communication and their own usage behavior when deciding whether or not to retain the service. We find that, compared to regular customers, the Net CLV of free-trial customers is much more responsive to direct marketing, advertising, flat-rate usage, and pay-per-use usage.

Therefore, companies should target direct marketing and advertising more to free-trial than to regular customers. In these marketing communications, it is advised to remind free-trial customers about their usage rates, especially when they are high, to make these customers even more likely to retain the service. For example, mobile phone providers could use direct marketing to communicate for how many minutes the customer has used the flat-rate service in the past period, cementing the relevance of the service. Companies could also try to enhance the actual usage of the service. For example, in the context of digital TV, firms could enhance usage opportunities by offering recorded TV shows or providing apps to watch TV on mobile devices.

Other service providers can estimate our retention and usage models to calculate the expected CLV for every customer, acquired by a free trial or not. They can then focus their marketing efforts on those customers with the highest expected return on marketing investment. If the estimation of the models is not feasible, our results suggest managers can rely on usage intensity as an indicator of customer value and a criterion for marketing allocation decisions.

This allows managers to distinguish between (likely) high- and low-value customers, especially within the free-trial group, because this group is most responsive to usage levels.

Our analysis also offers insights on the factors playing a role when considering the launch of a free-trial campaign. We show how the company can obtain an indication of the free trial's required expansion effect on the customer base to compensate for free-trialists' lower lifetime value and make the free-trial campaign worthwhile. Specifically, relative to a situation with only the regular offer, the number of adopters should increase by a factor that can be calculated as the expected CLV of regular customers divided by the expected CLV of free-trial customers. If the company expects the free trial to attract more customers than this factor prescribes, the trial offer may be a viable strategy. Importantly, the company can lower this break-even factor through targeted retention efforts after acquisition.

Future Research

Our work is the first to investigate the effects of free-trial acquisition on customer behavior and CLV, and therefore leaves several opportunities for further research. First, because this study is based on observational data, we need to control for selection effects – a challenge intrinsic to many studies examining the behavior of distinct customer groups (e.g., Gensler, Leeftang, and Skiera 2012). Alternatively, researchers may use controlled field experiments. One setting particularly suited for field experiments are online services, where individual consumers can be randomly assigned to different offers, and where the likelihood of consumers becoming aware of alternative offers is limited. At the same time, such an approach would still not guarantee full comparability of free-trial and regular customers because the researcher cannot *force* consumers to accept an offer.

Second, controlled experiments would also allow for the uncovering of the underlying

psychological processes that are likely to play a role. One interesting observation worthy of further attention is that free-trial customers are more heterogeneous than regular customers, for example in terms of CLV and responsiveness to marketing and usage. We speculate that the segment of free-trial customers includes not only people who are truly doubtful about their commitment, but also opportunistic consumers who would have adopted the service anyhow and just subscribe to the trial to enjoy the free months. Future research can further investigate the heterogeneity in the motivations of free-trial and regular consumers.

Third, future work could replicate this research in other contexts. Many Internet companies currently operate under a freemium model, in which customers can choose between a “free service” and a “premium service” which comes at a fee but provides enhanced functionality (Pauwels and Weiss 2008). For example, the on-demand streaming service Spotify offers temporary one-month free trials for their premium service, next to its (permanent) free service.

Fourth, future research may give a more complete account of the profitability implications of free-trial and regular acquisition. For example, for a news site, usage may be a source of advertising revenues (e.g., the number of page views may determine advertising income). Furthermore, it may be worthwhile to also include other value-creating behaviors (Verhoef, Reinartz, and Krafft 2010). Notably, one could examine whether free-trial and regular customers differ in the extent to which they engage in word-of-mouth communication.

In summary, we uncover the implications of free-trial acquisition for customer retention and CLV. We show how service usage and marketing activities drive consumers’ retention decisions and CLV, and how free-trial acquisition moderates these relationships. Our findings offer managers new insights on how to retain customers acquired through free trials.

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FOOTNOTES

¹ According to economic theory, the lower marginal consumption cost of a two-part (as opposed to pay-per-use) tariff structure should lead to *higher* usage rates. Iyengar et al. (2011) explain their counterintuitive finding by pointing out that partitioned prices draw consumer's attention and make them more price-sensitive.

² The remaining 29% is captured by smaller players, operating through satellite or via cable.

³ We measure a customer's *active* use of the flat-rate service by using monthly zaps. We also have a partially observed measure of a customer's *passive* use. Specifically, for a period of just 6 months, we observe the variable *hours*, capturing the monthly number of hours that the set-top box was switched on. However, this may not be an accurate indication of the time that the customer actively watched TV. In fact, it was technically possible to switch off the TV while leaving the set-top box switched on, making this variable less than ideal. For the months in which we have both *zaps* and *hours*, we find a significant positive correlation of .66 ($p < .01$).

⁴ We also estimate a retention model with lagged effects of DM and Adv., leaving model fit virtually unaffected ($\Delta\text{Hit probability} = .0002$, $\Delta\text{Top-decile lift} = -.0418$, $\Delta\text{Gini} = .0016$). We thus opt for the more parsimonious model (1).

⁵ To account for differences in the length of each month and the occurrence of holidays, we also estimate retention and usage models with monthly dummy variables. However, the results are very similar and model fit hardly changes ($\Delta\text{Hit probability} = .0004$, $\Delta\text{Top-decile lift} = -.0748$, $\Delta\text{Gini} = .0009$, $\Delta\rho_{\text{Flat-rate}} = .0242$, $\Delta\rho_{\text{Pay-per-use}} = .0031$). In addition, the model becomes cumbersome to estimate with 66 seasonality parameters (11 heterogeneous month coefficients in three equations). We therefore stick to the more parsimonious model (1).

⁶ We also estimate models in which we allow direct marketing and advertising to affect service usage but this does not lead to a notable improvement in model performance ($\Delta\rho_{\text{Flat-rate}} = -.0020$, $\Delta\rho_{\text{Pay-per-use}} = .0137$).

⁷ To check whether we should structurally account for any correlation between the slope coefficients, we inspect the correlations between the consumer-specific posterior slopes (Train 2009) and find the mean absolute correlation to be very small (.0084). Further, the low correlation between the residuals of the usage models (.0970) suggests that, after controlling for cross-sectional correlation, there is not much interdependency between the error terms left.

⁸ Following Park and Gupta (2012, footnote 3 and expression 10), we use empirical instead of estimated densities to generate $\widehat{DM}_{it}$ and $\widehat{Adv}_{it}$. To keep estimations tractable, we treat DM as a continuous variable and use regular standard errors instead of bootstrapped ones (shown to be virtually the same, see Park and Gupta 2012). We test the retention model on a simulated data set with endogenous regressors and recover the true parameters well.

⁹ In the models in which we correct for both temporal and cross-sectional correlation, we compute $\widehat{DM}_{it}$ using the *mean-centered* direct-marketing variable: mean-centering ensures that we only retain that part of the original direct-marketing variable that may be correlated with the error term ξ_{it} in Equation 1 (Mundlak 1978).

¹⁰ From the 12,612 free-trial customers in the data set, we eliminate two customers because their propensity scores do not lie within the region of common support, a region defined as the overlap between the propensity score distributions of the two customer groups (Gensler, Leeflang, and Skiera 2012).

¹¹ Because free-trial customers may be particularly likely to churn in their first three months, we re-estimate the model only with customers who "survived" the first three months. The results are robust to this alternative specification ($\alpha_1 = -.040$, $z = -3.390$, $p < .001$).

¹² We test whether the marketing response estimates are affected by the inclusion of customers who churn already during the first months after acquisition. Leaving out these customers yields comparable results ($\alpha_8 = .046$, $z = 2.30$, $p < .05$; $\alpha_9 = .08$, $z = 5.11$, $p < .001$, both one-tailed).

¹³ The carry-over coefficients for the two usage components are not directly comparable because we use a log-log regression for flat-rate usage and a zero-inflated Poisson model for the pay-per-use service. Nonetheless, the relative magnitude of the coefficients suggests that the flat-rate service is characterized by higher state-dependence than the pay-per-use service. This is consistent with the idea that consumers get used to watching the same television shows or series (flat-rate usage) but rather irregularly consume unrelated content from the VOD service (pay-per-use).

¹⁴ The relative results remain the same when we vary the simulation horizon or discount rate.

¹⁵ We compute customer-specific arc elasticities for a 1% increase in the focal variable in the first period after acquiring the customer, and apply a 95% Winsorization on estimated Net CLV elasticities to make sure that the summary statistics are not driven by outliers (Luo, Raithel, and Wiles 2013). Differences in elasticities between free-trial customers and regular customers are higher than what perhaps could be expected on the basis of the estimated coefficients (e.g., .310 for regular customers, and .310 + .154 for free-trial customers in the case of advertising). However, due to differences in the Net CLV *base* levels between the two customers groups, the same absolute lift in Net CLV represents a much higher percentage lift for a free-trial customer than for a regular customer.

Table 1

COMPARISON OF THIS PAPER WITH EXISTING STUDIES ON THE RELATIONSHIP BETWEEN ACQUISITION MODE AND CUSTOMER BEHAVIOR

	Acquisition Mode	Inclusion Usage Behavior	Impact of Acquisition Mode on Response to Retention Efforts	Correction for Selection	Relevant Findings with Regard to Impact on Customer Behavior
Channel Impact					
Verhoef and Donkers (2005)	Acquisition via Internet, direct-response advertising, and direct marketing (and more)	-	-	-	Acquisition through direct mail or direct-response commercials leads to lower retention rates than online acquisition.
Steffes, Murthi, and Rao (2008)	Online and direct-marketing channels (direct mail, direct selling, telesales)	-	-	-	Acquisition through direct mail yields highest retention rates.
Steffes, Murthi, and Rao (2011)	Online vs. direct-marketing channels (direct mail, direct selling, telesales)	-	-	✓	Online channel leads to customers with higher transaction amounts.
Referral Impact					
Villanueva, Yoo, and Hanssens (2008)	Word-of-mouth vs. marketing-induced acquisition	-	-	-	Customers acquired through word-of-mouth stay longer with the firm and generate more future referrals than other customers.
Chan, Wu, and Xie (2011)	Acquisition from Google advertising	-	-	-	Customers referred from Google search advertising have greater retention and transaction rates than other customers.
Schmitt, Skiera, and Van den Bulte (2011)	Acquisition via referral program	-	-	-	Customers attracted via referral program have higher retention rates than other customers.
Pricing/Sales Promotion Impact					
Anderson and Simester (2004)	Acquisition with price discount	-	-	-	Promotionally acquired customers choose cheaper products but buy more (often).
Lewis (2006)	Acquisition with price discount	-	-	-	Promotionally acquired customers have lower retention rates.
Iyengar et al. (2011)	Acquisition under two-part vs. pay-per-use pricing	✓	-	Not necessary ^a	Customers acquired under two-part pricing have lower usage and retention rates than customers charged on pay-per-use basis.
This paper	Acquisition with free trial	✓	✓	✓	Free-trial customers have higher churn rates and lower CLV, but are more responsive to marketing communication and to own usage behavior.

^a Customers are randomly assigned to one of two pricing structures.

Table 2
DESCRIPTIVE STATISTICS FOR FREE-TRIAL AND REGULAR CUSTOMERS

	Free-Trial Customers		Regular customers	
	Mean	(SD)	Mean	(SD)
<i>Dependent variables</i>				
Retention probability	.93	(.25)	.96	(.19)
Usage of flat-rate service (channel zaps)	169.35	(176.90)	189.28	(183.80)
Usage of pay-per-use service (number of videos-on-demand)	.73	(2.19)	.58	(1.91)
<i>Marketing communication</i>				
Direct marketing (number of direct-marketing contacts)	.34	(.55)	.16	(.41)
Advertising (share-of-voice)	.74	(.28)	.79	(.26)
<i>Customer-specific variables</i>				
Age (years)	46.22	(12.64)	44.89	(12.60)
Household size	2.98	(1.48)	2.88	(1.53)
Annual income (in €10,000)	2.44	(.56)	2.43	(.59)
Time-to-adoption (in months following the launch of the service)	13.14	(2.45)	12.38	(2.20)
<i>Control variables</i>				
Monthly subscription fee (in €)	9.66	(7.80)	13.22	(4.85)
Cancellation penalty (Termination Fees – Future Fees, in €)	-59.80	(68.08)	-8.14	(25.02)
VOD credit (in €)	5.50	(8.90)	1.38	(5.08)
Temperature (in °C)	12.82	(4.97)	12.83	(4.99)
Time-since-adoption (in months)	5.34	(3.52)	5.95	(3.68)
Direct-marketing contacts prior to acquisition	.62	(.61)	.26	(.48)
Advertising (share-of-voice) prior to acquisition	.73	(.27)	.76	(.27)
Total fees for regular 12-month contract at the time of acquisition (in €)	193.83	(50.04)	181.97	(44.79)
Number of customers	12,612		3,900	

Table 3
SELECTION OF MODEL FOR RETENTION DECISION

	M1 (selected model)	M2	M3	M4
<i>Model specification</i>				
Correction for selection	Matching	Matching	Joint estimation	Joint estimation
Correction for marketing endogeneity	Copula + Mundlak	Copula only	Copula + Mundlak	Copula only
<i>Hypothesis testing</i>				
H ₁ : Trial effect on Retention < 0	-.278 ***	-.106 ***	-.255 ***	-.066 ***
H _{2a} : UsageFR × Trial effect > 0	.040 ***	.107 ***	.008	.056 ***
H _{2b} : UsagePPU × Trial effect > 0	.013 **	.015 **	.008 *	.013 **
H _{3a} : DM × Trial effect > 0	.133 ***	.057 ***	.096 ***	.051 ***
H _{3b} : Adv × Trial effect > 0	.154 ***	.150 ***	.150 ***	.134 ***
<i>Model fit</i>				
<i>Hit probability^a</i>				
In-sample	.917	.914	.908	.904
Out-of-sample (cross-sectional)	.922	.913	.904	.904
Out-of-sample (longitudinal)	.953	.918	.948	.952
<i>Top-decile lift</i>				
In-sample	5.853	5.308	5.776	5.153
Out-of-sample (cross-sectional)	7.111	5.130	5.800	5.306
Out-of-sample (longitudinal)	4.244	3.055	4.453	5.219
<i>Gini coefficient</i>				
In-sample	.755	.713	.748	.707
Out-of-sample (cross-sectional)	.826	.711	.752	.706
Out-of-sample (longitudinal)	.578	.402	.568	.664

Notes: *** $p < .001$; ** $p < .05$; * $p < .1$ (all one-sided).

^a We highlight the best model fit in bold. To compute out-of-sample fit measures, we reestimate the model on a random cross-section of 70% of the customers, or on the first 70% of the longitudinal observations, and compute model fit for the holdout sample.

Table 4
MODEL FIT FOR SELECTED MODEL (M1)

	Hit probability	Retention Top-decile lift	Gini coefficient	Flat-rate usage Correlation between actual and predicted	Pay-per-use Correlation between actual and predicted
<i>In-sample fit</i>					
Free-trial customers	.899	5.696	0.750	.811	.750
Regular customers	.932	5.634	0.750	.815	.740
<i>Out-of-sample fit (cross-sectional)^a</i>					
Free-trial customers	.906	6.946	0.821	.809	.724
Regular customers	.936	7.052	0.819	.815	.727
<i>Out-of-sample fit (longitudinal)^b</i>					
Free-trial customers	.948	4.526	0.599	.751	.673
Regular customers	.958	3.785	0.545	.778	.593

^a We reestimate the model on a random draw of 70% of the customers and compute model fit for the holdout sample.

^b We reestimate the model on the first 70% of the longitudinal observations, and predict usage and retention for the holdout sample.

Table 5
ESTIMATION RESULTS^a

		Population Mean		Standard Deviation	
		Estimate (SE)		Estimate (SE)	
Retention					
Intercept		3.034	(.006)	.025	(.018)
Age		-.002	(.000)		
Household size		-.037	(.002)		
Income		.059	(.002)		
Time-to-adoption		-.002	(.000)		
Trial	H ₁ : effect < 0	-.278	(.008)	.016	(.021)
Flat-rate usage		.728	(.006)	.333	(.006)
× Trial	H _{2a} : effect > 0	.040	(.009)	.159	(.015)
Pay-per-use usage		.039	(.004)	.015	(.005)
× Trial	H _{2b} : effect > 0	.013	(.005)	.010	(.007)
Direct marketing		1.565	(.012)	.190	(.034)
× Trial	H _{3a} : effect > 0	.133	(.014)	.086	(.043)
Advertising		.310	(.008)	.000	(.027)
× Trial	H _{3b} : effect > 0	.154	(.011)	.080	(.033)
Copula correction term for DM		-.596	(.005)		
Copula correction term for Adv		-.017	(.002)		
Mundlak correction term for DM		-2.111	(.014)		
<i>Control variables</i>					
Initial period		-1.377	(.007)	-.040	(.016)
Monthly subscription fee		-.008	(.000)	.001	(.001)
Cancellation penalty		.003	(.000)	.000	(.000)
Temperature		.012	(.000)	.000	(.001)
log(Time-since-adoption)		-.572	(.004)	.022	(.014)
Flat-rate usage (log zaps)					
Intercept		5.609	(.006)	.881	(.005)
Age		.000	(.000)		
Household size		.036	(.002)		
Income		-.034	(.002)		
Time-to-adoption		-.048	(.000)		
Trial		-.269	(.008)	-.081	(.014)
<i>Control variables</i>					
log(Monthly subscription fee)		-.033	(.002)	.004	(.004)
log(Temperature)		-.417	(.002)	-.016	(.004)
log(Time-since-adoption)		-.319	(.003)	.340	(.004)
lagged log(Flat-rate usage)		.242	(.001)	-.005	(.002)
log(sigma)		-.007	(.002)		
Pay-per-use (VODs)					
Intercept (incidence)		-.140	(.006)	1.410	(.004)
Intercept (amount)		-.243	(.007)	1.245	(.018)
Age		-.014	(.000)		
Household size		.090	(.002)		
Income		.042	(.003)		
Time-to-adoption		-.018	(.001)		
Trial		.113	(.010)	.016	(.015)
<i>Control variables</i>					
Monthly subscription fee		-.006	(.000)	.001	(.000)
VOD credit		.005	(.001)	-.008	(.001)
Temperature		-.005	(.000)	.015	(.001)
log(Time-since-adoption)		.053	(.003)	-.156	(.004)
lagged Pay-per-use		.023	(.000)	-.008	(.000)

Log-likelihood: -310,958; N: 196,251; BIC: 622,892; AIC: 622,077.

^a Numbers in bold are significant at the $p < .05$ level (two-sided).

Table 6
IMPROVING RETENTION RATES AND CUSTOMER EQUITY

	Impact for targeted customers (20%)		Impact for entire customer base (100%)	
	Impact on retention ^a	Impact on Net CE ^b	Impact on retention ^a	Impact on Net CE ^b
<i>Increase direct marketing efforts by €0.5 for 20% of the customers</i>				
Scenario 1: No targeting (random)	158.0%	115.9%	31.6%	23.0%
Scenario 2: Target free-trial customers (random)	186.7%	136.0%	37.3%	27.2%
Scenario 3: Target regular customers (random)	95.6%	75.6%	19.1%	15.1%
Scenario 4: Target customers based on highest individual- level response coefficients	181.4%	132.9%	36.3%	26.6%

^a Number of retained customers in month 36 after the start of the free-trial program.

^b Net Customer Equity for retained customers in month 36 after the start of the free-trial program.

Figure 1
CONCEPTUAL FRAMEWORK

Figure 2
MODEL FIT

Figure 3
DISTRIBUTION OF EXPECTED SURVIVAL TIMES
FOR FREE-TRIAL AND REGULAR CUSTOMERS

Notes: To calculate survival times, we consider a maximum time horizon of three years (36 months).

Figure 4

NET CUSTOMER LIFETIME VALUE FOR FREE-TRIAL AND REGULAR CUSTOMERS

Figure 5

RESPONSIVENESS TO MARKETING COMMUNICATION

Notes: We compute arc elasticities for a 1% increase in, respectively, advertising, direct marketing, and usage levels in month 4 after acquiring the customer (i.e., after the trial period).

Figure 6

REQUIRED IMPACT OF FREE TRIALS ON CUSTOMER BASE EXPANSION
FOR DIFFERENT LEVELS OF MARKETING

Notes: κ represents the threshold value to keep customer equity constant, and can be interpreted as how much more successful the free trial should be at attracting new customers compared to the regular offer.

WEB APPENDIX

A. Correlations Between Independent Variables

CORRELATION MATRIX												
	1	2	3	4	5	6	7	8	9	10	11	12
1. Trial dummy	1.00											
2. Direct marketing	.15***	1.00										
3. Advertising	-.08***	-.04***	1.00									
4. Age	.05***	.03***	-.09***	1.00								
5. Household size	.03***	.02***	.00	-.10***	1.00							
6. Income	.01	.04***	-.24***	.11***	.04***	1.00						
7. Time-to-adoption	.14***	.15***	.00	.01***	.07***	.02***	1.00					
8. Subscription Fee	-.22***	-.09***	-.03***	-.02***	-.03***	.00	-.14***	1.00				
9. Cancellation penalty	-.36***	-.11***	.00	-.03***	-.04***	-.01**	-.26***	.76***	1.00			
10. VOD credit	.22***	.07***	.02***	.00	.04***	.00	.27***	-.70***	-.62***	1.00		
11. Temperature	.00	.08***	.07***	.00	-.01	-.01	-.21***	-.31***	-.25***	.20***	1.00	
12. Time-since-adoption	-.08***	-.07***	-.03***	-.02***	-.04***	-.01***	-.29***	.71***	.79***	-.56***	-.17***	1.00

Significance levels (two-tailed): *** $p < .001$, ** $p < .01$.

The corresponding variance inflation factors (VIFs) do not exceed 10 in any of the models (Hair et al. 2010).

B. Parameter Estimates for the Propensity Model in the Matching Procedure

ESTIMATION RESULTS FOR THE PROPENSITY SCORE MODEL ^a		
	Estimate (SE)	
Intercept	.315	(.011)
Age	.005	(.000)
Household size	.027	(.003)
Income	-.072	(.004)
Time-to-adoption	.009	(.001)
Direct marketing	.649	(.017)
Advertising	-.426	(.014)
Subscription fee	.001	(.000)
Log-likelihood: -8,357; N: 16,512; BIC: 16,792; AIC: 16,731		
^a Numbers in bold are significant at the $p < .05$ level (two-sided).		

C. Estimated Correlations Between Random Intercepts of Retention and Usage Models

ESTIMATED CORRELATIONS BETWEEN RANDOM INTERCEPTS ^a				
	Correlation coefficient (SE)			
	1	2	3	4
1. Retention				
2. UsageFR	.083 (.011)			
3. UsagePPU	-.117 (.005)	.033 (.006)		
4. Zero-inflation model of UsagePPU	-.058 (.028)	.279 (.011)	.728 (.011)	
^a Numbers in bold are significant at the $p < .05$ level (two-sided).				

D. Computation of Net CLV

We compute a customer's Net CLV as the discounted value of the expected future profits minus the costs to acquire that customer:

$$(8) \quad \text{Net CLV}_i = \sum_{t=1}^{36} \frac{S_{it} \times m_{it} + (1 - S_{it}) \times P_{it}}{(1+d)^t} - AC_i,$$

where S_{it} is the survival probability of customer i in month t after acquisition, m_{it} is the customer's expected profit if he or she retains the service in month t , P_{it} is the penalty (in €) the customer has to pay when he or she terminates the contract in month t (zero during a trial and from month 12 onward), AC_i refers to the customer's acquisition costs, and d is the monthly

discount factor. d corresponds to an annual rate of 8.5%, which is a common value for the weighted average cost of capital of TV content providers such as Netflix, Comcast, and DirecTV (e.g., Cusick et al. 2014; Swinburne, Khadilkar, and Yeh 2014).

Notice that the survival probability S_{it} in month t is based on the customer's retention decisions in the preceding months: $S_{it} = \text{Prob}(r_{i,0}, \dots, r_{i,t-1} = 1)$. Furthermore, the expected margin m_{it} in a given month equals the revenue generated by the customer, less the costs to retain the customer (Reinartz, Thomas, and Kumar 2005):

$$(9) \quad m_{it} = \underbrace{\text{Fee}_{it}^{\text{sub}} + \overline{\text{Fee}}^{\text{PPU}} \times \text{UsagePPU}_{it}}_{\text{Revenue}} - \underbrace{\overline{\text{Costs}}^{\text{DM}} \times \text{DM}_{it} - \overline{\text{Costs}}^{\text{Adv}}}_{\text{Costs}},$$

where $\text{Fee}_{it}^{\text{sub}}$ is the monthly subscription fee of €15.95 that customer i has to pay in month t (zero during a free-trial period), $\overline{\text{Fee}}^{\text{PPU}}$ is the average per-unit fee for the pay-per-use service corrected for average per-unit content cost (€3 minus €0.25 throughout the simulation period¹), UsagePPU_{it} refers to the customer's expected consumption amount (in units) of the pay-per-use service in month t , DM_{it} is the number of direct-marketing contacts with the customer in month t , $\overline{\text{Costs}}^{\text{DM}}$ is the average cost for a single contact, and $\overline{\text{Costs}}^{\text{Adv}}$ is the average monthly advertising cost per customer.

To determine AC_i , $\overline{\text{Costs}}^{\text{DM}}$, and $\overline{\text{Costs}}^{\text{Adv}}$, we need to allocate the observed marketing efforts between acquisition and retention (Gupta, Lehmann, and Stuart 2004). Because we observe consumer-specific direct-marketing efforts before and after acquisition, we can readily compute the acquisition and retention direct-marketing costs for each customer by multiplying

¹ To obtain an estimate of content costs for streamed VODs, we divide Netflix's cost of revenue in 2013 (\$2.6bn) by the number of hours of watched content in that year (12bn), resulting in content costs of \$.22 per streamed hour (Netflix 2014). At an average length of 90 minutes per VOD (Huang, Li, and Ross 2007), content costs amount to \$.33 per VOD (approximately €0.25).

the relevant number of direct-marketing contacts by the average delivery cost of €0.37.² Notice that the average observed monthly number of marketing contacts for customer *acquisition* is .62 for free-trial, and .26 for regular customers. The company uses direct marketing less often for customer *retention*: once acquired, free-trial and regular customers are contacted on average .34 and .16 times per month, respectively. In line with Gupta, Lehmann, and Stuart (2004), we use these average retention efforts when simulating future behavior beyond the observation period.

We also need to split the expenditures on mass advertising into retention and acquisition costs. We divide the monthly total advertising budget between retention and acquisition proportionally to the numbers of iTV adopters and non-adopters in the company's total customer base (see Gupta, Lehmann, and Stuart 2004). We then distribute the acquisition advertising budget over the company's new customers and the retention advertising budget over the already acquired customers. On average, the company spends €169.61 on advertising to acquire a new customer. This number is close to the US\$181.8 reported in Libai, Muller, and Peres (2009) for another telecommunication provider in the same geographical region. The monthly advertising cost for retaining a customer is €0.51, and thus substantially lower than the acquisition cost (see Thomas 2001). Other fixed costs are not directly related to the number of customers or their usage intensity (e.g., the network infrastructure which is owned by the company), and hence can be ignored in the computation of Net CLV.

² The number of iTV customers was small relative to the company's entire customer base (which mainly includes telephone and Internet subscribers), so that we can safely assume that the already existing service employees handled iTV customers as well. As a result, direct-marketing costs correspond to the actual delivery costs of the messages. There are three channels for direct marketing in the data set: postal mail, outbound calls, and e-mail. We take actual postal fees of the National Post in 2004 (€0.44 for non-priority delivery), contact time of the average phone call (6.39 minutes for non-technical inquiries; Sun and Li 2011) multiplied by the per-minute call fee of the national carrier in 2004 (€0.051), and a nominal amount of €0.01 to reflect the small delivery costs of emails (Danaher and Dagger 2013). Finally, we weight the delivery costs by the relative occurrence of the respective channels in the data set and arrive at an average direct-marketing cost of €0.37 per contact.

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