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Customer defection due to service elimination and post-elimination customer behavior: An empirical investigation in telecommunications

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ABSTRACT

Service industries require rapid innovations in their service portfolios to gain and maintain competitive advantages. Service elimination is a potential tool for portfolio renewal, though it might threaten increased defection rates. To contribute to both service elimination and customer defection literature, this paper proposes a model of customer responses to service elimination, with practical implications for decision-makers in rapidly innovating telecommunication markets.

In particular, the main study, conducted in the context of Hungary's telecommunications sector, reveals that customers' tenure, usage intensity, and age reduce the negative effects of a price increase on their defection; the price increase, degree to which customers interact with service providers, customer defection, and competitive effects in turn increase post–service elimination usage intensity.

These findings suggest implementation strategies that can reduce customer defection following price increase due to service elimination, by focusing on new customers, light users, and the quality of customer interactions.

Keywords: service elimination; customer defection; switching cost; telecommunication services; Heckman sample selection

1. INTRODUCTION

Consider the following description, provided from a customer's perspective: "*Erste Bank* called me last week to tell me that the 'conditions had changed' at the bank: my current '*Joker*' credit card will be eliminated but they can offer a new credit card instead of my current one."[5] That is, the customer learns that a current service offering is being eliminated and will not be available any longer, so the customer must migrate to a new and typically more expensive service. Most consumers have encountered a similar situation, which raises questions about how they react. How do they decide whether to accept the new offer or switch to another service provider? How do they act and use the service, if they decide to stay? If they must pay a higher monthly fee for the new service, can they still be satisfied? To address these questions, we seek to establish a model of the factors that influence customer defection responses to service eliminations. We include the customer's tenure with the firm, their interaction intensity during the service elimination experience, prior service usage intensity, and age, as well as the features of the replacement service, such as whether it offers more or less value and benefits or comes with a price change. With this model, we also predict post–service elimination customer behavior among those who decide to stay.

For these efforts, we establish a precise definition of service elimination, as a process by which a service firm eliminates existing services and tries to migrate existing customers to new service packages. The process likely aims to foster service innovation (Argouslidis & McLean, Service elimination decision-making: Analysis of candidates for elimination and remedial actions, 2003), though many service elimination projects are at risk of failure, if a large portion of the customer base churns in response to the service elimination. An ad hoc service elimination process that fails

[5] Review by an Erste Bank customer on homar.blog.hu

to meet customer’s needs, offers poor communication, or does not allow for sufficient interaction will not satisfy customers. Furthermore, price perceptions likely drive customer defection. Thus despite their promise for service innovation, many service providers delay or avoid any service elimination, thus these projects are often delayed or not even launched.

Such challenges also might explain why service elimination outcomes are so rarely studied in services marketing (Papastathopoulou, Gounaris, & Avlonitis, 2012). A few studies address pre-elimination decision-making (Argouslidis, 2006) or service elimination decision-making processes (Harness & Marr, 2004), primarily from the firm’s perspective (Papastathopoulou et al., 2012). That is, previous research outlines some outcomes of service elimination on the firm level, but it has not established which factors are required to ensure a successful project or how firms might encourage customers to stay loyal to them after the service elimination. An important open question pertains to how service elimination outcomes might be influenced by competitive effects (Kent & Argouslidis, 2005), such that the availability of viable alternatives seems likely to determine customers’ post-elimination behavior.

In identifying these research gaps, we establish three main research questions that the current paper seeks to address: (1) What factors might reduce the effects of a price change on customer defection in the case of a service elimination? (2) How do customers’ behaviors change, between the pre- and post-elimination stages? (3) What strategies can firms develop to ensure the success of their service elimination projects?

In particular, we predict that service elimination accelerates service innovation cycles, which is a priority for service companies, but service innovation also usually imposes a price change. Accordingly, the service elimination process arguably should be planned together with service innovation efforts (Argouslidis & Baltas, 2007), to avoid efficiency and revenue losses and ensure that maintenance and development costs remain relatively low. Analyzing eliminated services also may produce important insights for developing new service portfolios. But beyond the innovation outcomes, service elimination clearly may have effects on the customer base, particularly if it leads to price changes, in that customers respond differently to price increases and decreases (Sivakumar & Raj, 1997). By retaining its existing customer base, the service provider can gain long-run revenue opportunities, in that customer retention is more profitable than customer acquisition (Palmer, 1998) due to lower levels of perceived risk, trust, and openness to change. Thus, another critical goal for any service elimination project must be to minimize customer defection.

Using these criteria for service elimination success, we investigate how customer factors can lead to specific service elimination outcomes. The results highlight that customer–firm interactions during the process should be tailored to customers' needs; in particular, their attributes (e.g., tenure, interaction intensity, usage intensity, age) moderate the link between a price change due to the service elimination and the success of the project. Second, it is important to note that business-to-consumer, business-to-business customers, and voice only and voice and data users differ in some relevant aspects in terms of service elimination success. We thereby advance the service elimination literature in at least two ways.

First, to clarify how the attributes of the service elimination project and customer factors can combine to motivate customers to remain loyal, we analyze a database from a telecommunications service provider, involving 10,056 customers. The results affirm that customer tenure, usage intensity, and age all help lower the risk of losing customers following a price change due to a service elimination. For service providers, these results offer relevant guidance: even if a price change is unavoidable in the course of a service elimination project, they can target specific user groups and interact with them more appropriately, to encourage their continued loyalty.

Second, this study offers the first investigation of the combined effects of a price change, interaction intensity, and competition on consumers' *post*-elimination usage behaviors. The only two prior service elimination research focusing on post-elimination behavior (Harness & Marr, 2004; Gounaris, Avlonitis, & Papastathopoulou, 2006) did not consider customer usage as an outcome variable. This novel approach reveals a previously unidentified outcome: a price increase, customer defection, and competitive effects together can increase post-elimination usage intensity. Therefore, firms can influence the level of post-elimination usage by their customers if they price the new offer optimally, while also engaging in overall tactics designed to motivate customers to stay.

In Section 2, we establish the theoretical background for our predictions about the relationships of price changes, tenure, interaction intensity, usage intensity, and post-elimination behavior, which we summarize in five hypotheses. Section 3 contains an overview of the studies. In Section 4, we present our main study, in which we analyze price increase effects on customer defection; a follow-up study in Section 5 addresses their post-elimination behaviors. Finally, we discuss the results, draw some conclusions, and point to some limitations and suggestions for further research in Section 6.

2. THEORY AND HYPOTHESES DEVELOPMENT

We predict that several customer factors moderate the relationship between price changes and customer defection, including tenure, interaction intensity, usage intensity, and age. Those interactions in turn might affect post-elimination customer usage intensity.

2.1. Tenure

Tenure reflects the time since the customer's enrollment in the service contract (Allison, 1995). A longer relationship generally corresponds to lower customer defection (Dawes, 2009; Dagger, Danaher, & Gibbs, 2009; Ngobo, 2005), and it also moderates the relationship between a price increase and customer retention (Dawes, 2009), for several reasons. In particular, psychologically loyal customers (Oliver, 1999) tend to block out competitive information, to avoid discomforting second thoughts about a prior decision. A long history of successful service provision also can lead the customer to establish a sense of interpersonal bonding (Gwinner, Gremler, & Bitner, 1998) or dependence (Bendapudi & Leone, 2003). Perceived risk provides another potential explanation (Burnham, 1998), in that customers who perceive higher risk tend to be more loyal than those with lower perceived risk levels (Helsen & Schmittlein, 1994). Because brand loyalty can reduce perceived risk (Roselius, 1971), loyal customers who appreciate this benefit also tend to be less sensitive to price changes (Helsen & Schmittlein, 1994), less likely to switch to a competitor even if the current supplier increases its price, and willing to spend more (Reichheld & Sasser, 1990). Relationship inertia also can encourage habitual buying (Wieringa & Verhoef, 2007), such that long tenured customers get used to their existing service and keep it, without explicitly considering alternatives. Inertia is not a rational decision-making process, so a price increase likely does not disrupt habitual behavior either. Overall then, these theorizations imply that price sensitivity should decrease with greater customer tenure (Reichheld & Teal, 1996; Reinartz & Kumar, 2000; Reinartz & Kumar, 2002; Dawes, 2009), and customers with longer tenure may be less affected by a price increase due to service elimination.

Hypothesis 1: The longer the tenure of the customer, the weaker the effect of service elimination price increase on customer defection

2.2. Interaction intensity

Interaction intensity is the degree to which customers interact with service providers, or how intensively both parties seek to communicate (Stringfellow, Teagarden, & Nie, 2008), directly or indirectly, for personal or business purposes (Crosby, Evans, & Cowles, 1990). It depends on several factors, reflecting both the customer's and service provider's perspectives. Some service benefits accrue only with lower levels of interaction intensity (Stringfellow et al., 2008), such as clear, straightforward overviews of relevant information and standardized processes. When processes establish explicit insights and follow in a sequential order, customers suffer less confusion and require less interaction with the service provider. But more intense interactions also can enhance satisfaction and trust (Bennett & Robson, 2004). Both process-based trust, related to past exchanges, and characteristic-based trust, tied to social similarity (Zucker, 1986) are higher following more intense interactions (Chen, Chen, & Tsung, 2007). Furthermore, intense interactions tend to support closer and longer relationships, greater commitment by both parties, and the involvement of top management (Hoffmann & Herstatt, 2005).

Accordingly, interaction intensity has implications for pricing. For customer-intensive services, customers' perceived value tends to increase with more social interactions, so service providers can charge higher prices or increase the speed of their provision, or both, which should increase their revenues (Li, Jiang, & Yuan, 2019). Through intense, personal contacts and interactions, competitive influences also might be mitigated, because customers enjoy the reduced ambiguity associated with competitive parameters such as price and quality (which is hard to evaluate) (Alvesson, 2001). Applying these insights to service elimination settings, we note that the project tends to be relatively unstandardized, featuring unknown parameters related to the available service offerings. Because more intense interactions increase customers' perceived value and commitment, we expect interaction intensity to weaken the effect of a potential price increase on customer defection.

Hypothesis 2: The higher the interaction intensity between customer and service provider, the weaker the effect of service elimination price increase on customer defection

2.3. Usage intensity

Usage intensity expresses the extent to which the customer uses the service, which can be calculated as some combination of usage frequency (Veríssimo, 2018), the number of services adopted in a given timeframe (Smego, Herning, Davis, Hossain, & Mohammed Al-Khusaiby, 2015), and the time spent on a regular basis using the service (Saleem & Ellahi, 2017). It is context specific, so for this paper, we define usage intensity, in a telecommunication setting, as all activities that individuals or households perform to take advantage of the services they have adopted (Cecere & Corrocher, 2011), which may depend on various factors (Grajek, Gugler, Kretschmer, & Mişcişin, 2019). First, consumer preferences are inherently heterogeneous. Second, if customers are more connected with one another, they use telecommunications networks more intensely. Third, substitute technologies that increase the breadth of service portfolios also can drive more intense usage. Fourth, the service portfolios offered by competitors might influence usage intensity for both individual service providers and the industry overall. With regard to the effects on price considerations, previous studies show that heavy users are less price sensitive than light users (Helsen & Schmittlein, 1994), and customers with higher usage intensity are less likely to switch, because they tolerate greater price increases than light users (Danaher, 2002).

Usage intensity could have other influences on the relationship between price increases and customer defection though. First, if usage intensity is result of additional service adoption, it might decrease negative perceptions of a price increase, because the price seems justified in return for the expanded service provision (Woisetschläger, Evanschitzky, & Holzmüller, 2008), Second, high income customers tend to use mobile services more intensively, such that the income differences between light and heavy users may explain heavy users' lower price sensitivity (Hawthorne & Grzybowski, 2019). In turn, we expect heavy users to be less sensitive to price increases.

Hypothesis 3: The higher the usage intensity of the customer, the weaker the effect of service elimination price increase on customer defection

2.4. Age

As people age, inertia effects may grow stronger, due to their decreasing interest in experimentation (von Wangenheim, 2004). Thus, age is associated with higher loyalty (Lambert-Pandraud, Laurent, & Lapersonne, 2005; Patterson, 2007) and customer retention (Idrees & Xinping, 2017; Koech & Namusonge, 2014; Mburu, 2014; Seo, Ranganathan, & Babad, 2008). As a consequence of inertia, previous studies also reveal a negative relationship between age and price sensitivity (Buchmueller, 2006). Accordingly, we expect weaker effects of price increases on defection by older customers.

Hypothesis 4: The higher the age of the customer, the weaker the effect of service elimination price increase on customer defection

2.5. Post-elimination behavior

In a pay-per-use system, usage intensity should be lower following a price increase, whereas in a subscription setting, according to equity theory, customers likely try to maintain equity in the input–output ratio (Adams, 1965; Deutsch, 1975). If customer inputs rise, due to a price increase, the customer may increase her or his usage, to compensate, or else exit the relationship (Bolton & Lemon, 1999). This argument is reasonable in telecommunication contexts, because access is inelastic, whereas usage (e.g., calls) is elastic (Briglauer, Schwarz, & Zulehner, 2011). Among those who remain with the service provider, we expect their usage levels to increase.

Hypothesis 5: Service elimination price increase is associated with a higher post-elimination usage intensity

3. OVERVIEW OF THE STUDIES

We present the predicted relationships among the independent variables in our model with the seven hypotheses in Figure 1, then conduct two studies to test these hypotheses.

In Study 1, we use Heckman sample selection (see Appendix 1) to determine which factors reduce the risk of customer defection following a price increase due to service elimination, then analyze customers' post-elimination behavior in response. Because empirical data about service elimination projects are rarely publically available, Study 1 identifies key insights using the real-life service elimination database of a telecommunications service provider.

However, this database does not include information about customers who leave following the service elimination, so with Study 2, we seek a better understanding of the post-elimination phase and also consider the potential influences of competitive offers. That is, in Study 2 we investigate how customer defection and competition affect customers' post-elimination usage behavior, using an experimental design in which we manipulate customer defection (loyal vs. defected) and competition (none vs. competitive offerings without differences vs. competitive offerings with differences) and measure post-elimination usage intensity intentions.

4. STUDY 1

To investigate factors that might reduce the risk of customer defection during a price increase due to service elimination situation, and specifically test Hypothesis 1-5, we turn to a real-world data set that includes information about a service elimination project, including changes in service conditions, price changes, and how the service provider interacted with customers. The available measure of interaction intensity does not differentiate the source that initiated the contact (customer or service provider) which represents a data limitation, but we have access to a range of customer-related information, such as tenure, usage intensity, caller satisfaction, age, location, household size, etc. As offers from other service providers might be more competitive in Western Hungary, we expect different churn rates according to locations due to differences according to economic development.

4.1 Model

For this empirical analysis, we anticipate a two-stage decision process, such that customer defection is the dependent variable in the first stage, and post-elimination usage intensity (i.e., logarithmic difference of minutes customers use before and after service elimination) is the dependent variable for the second stage. To start, we consider which factors might determine the probabilities that customers stay with the company following a price increase due to service elimination. Table 1 lists all the variables in the empirical model.

The price change reflects the difference between in prices for the old versus innovated service. In line with our predictions that tenure, interaction intensity, usage intensity, and age reduce the effect of a price increase on customer defection, we include the main and interaction effects with price for each predictor in the model. To control for other possible effects, we also include control variables, such as switching barriers, satisfaction, regional location, city size, and household size, but we formulate no hypotheses related to these principally demographic data. Noting missing values in the database for some variables, we use dummies to account for any notable differences due to missing data. Therefore, in the first step, we use the model to estimate drivers of customer defection, as follows (Heckman procedure):

$$\begin{gathered}\textit{Customer defection} = (1 \text{ or } 0) = \gamma_0 + \gamma_1 \textit{Price\_increase} + \gamma_2 \textit{Price\_increase x Tenure} + \gamma_3 \\ \textit{Price\_increase x Interaction\_intensity} + \gamma_4 \textit{ Price\_ increase x Pre\_elimination\_Voice\_usage} + \gamma_5 \\ \textit{Price\_increase x Pre\_elimination\_Data\_usage} + \gamma_6 \textit{ Price\_ increase x Age} + \\ \gamma_7 \textit{Tenure} + \gamma_8 \textit{Interaction\_intensity} + \gamma_9 \textit{Interaction\_intensity\_Dummy} + \\ \gamma_{10} \textit{Pre\_elimination\_Voice\_usage} + \gamma_{11} \textit{Pre\_elimination\_Data\_usage} + \gamma_{12} \textit{Age} + \gamma_{13} \textit{Age\_Dummy} + \\ \gamma_{14} \textit{Switching\_barriers} + \gamma_{15} \textit{Satisfaction} + \gamma_{16} \textit{Satisfaction\_Dummy} + \gamma_{17} \textit{Regional\_location} + \\ \gamma_{18} \textit{Size\_of\_city\_location} + \gamma_{19} \textit{Price\_increase x Size\_of\_city\_location} + \gamma_{20} \textit{Household\_size} + \\ \gamma_{21} \textit{Household\_size\_Dummy} + u_1.\end{gathered}$$

Then in a second step, we seek to estimate which factors determine differences in usage intensity after service elimination. The difference in the minutes of talk time the customer uses, before and after service elimination, reflects changes in customer behavior. However, customers who stay with the company after service elimination do not represent a random sample; we address these methodological issues in the next section. The specification for the second-stage equation, which again includes control variables, is as follows:

$$\begin{gathered} \textit{Usage\_intensity\_difference} = \beta_0 + \beta_1 \textit{Price\_ increase} + \beta_2 \textit{Interaction\_intensity} + \\ \beta_3 \textit{Interaction\_intensity\_Dummy} + \beta_4 \textit{Tenure} + \beta_5 \textit{Pre\_elimination\_Voice\_usage} + \\ \beta_6 \textit{Pre\_elimination\_Data\_usage} + \beta_7 \text{Age} + \beta_8 \textit{Age\_Dummy} + \beta_9 \textit{Satisfaction} + \\ \beta_{10} \textit{Satisfaction\_Dummy} + \beta_{11} \textit{Regional\_location} + \beta_{12} \textit{Size\_of\_city\_location} + \beta_{13} \textit{Household\_size} + \\ \beta_{14} \textit{Household\_size\_Dummy} + u_2 \end{gathered}$$

We furthermore assume that $u_1 \sim N(0,\sigma)$, $u_2 \sim N(0,1)$ and $corr(u_1, u_2) = \rho$.

4.2 Data

In accordance with a research agreement between the service provider and the first author's university, we obtained study data from one of three telecommunications operators in Hungary, which underwent a substantial service package simplification project in 2012–2013. The services eliminated included outdated options, which were replaced with newer offers, as well as some technical service alternatives to the provider's core services that had become redundant. In total, the eliminations involved 25 mobile service packages (no fixed line or other services) for consumers and 62 packages targeting business clients. These eliminations affected 10,065 customers total.[6] In the consumer segment, services are standardized, whereas for business customers, they are personalized. From the overall sample of affected customers, 1585 churned,

[6] In line with the research contract with the service provider, only broad sample data are available.

indicating a churn rate of 15.76%, significantly higher than the 2% industry average (ClintWorld GmbH., 2013). Price increases in 45% of the cases and price decreases in 55% of the cases, which can be considered as a balanced sample. Similarly to Western Hungarian location, bigger cities also might have a greater variety of competitor offers that influences churn rates.

4.3 Data quality

Due to a data omission problem for non-churned customers, some part of the database had to be modified. That is, customers who stay after the service elimination entered into a new contract, so their monthly fee should be known. In certain cases though, these data were missing, and the company was not able to reproduce valid data. To impute these missing new monthly fee data, we determined which service package the customers chose, then identified the typical new monthly fees across that particular package group. By comparing their old against their imputed new monthly fees, we calculate the logarithmic monthly fee differences. However, out-of-bundle fee data were not available, so even with this imputation, we have to rely on fixed monthly fee changes only. We found no other obvious errors in the rest of the database.

4.4 Results

The empirical results are in Tables 2 and 3. In addition to estimating the probabilities of customer defection (first stage) and differences in usage behavior among remaining customers (second stage) according to our first two research questions, we distinguish the differences across four major segments to capture usage patterns more precisely: business-to-business (B2B), business-to-consumer (B2C), voice only and voice and data segments. The results for the B2C and B2B segments reflect the service packages that customers use; whereas all the B2C services are publically available, some B2B services are personalized for just a particular business client. For voice-only users, we contrast their service usage against that of customers whose subscriptions contain both voice and data. The detailed results obtained from the different models for these subsamples are available in the Web Appendix (Table 1).

We first turn our attention to answer our first research question related to the effects of a service elimination price increase on customer defection. Table 2 contains the first-stage results of the maximum likelihood Heckman procedure (details on this methodology can be found in Appendix 1), revealing that a the price increase raises the risk of customer defection, as would generally be expected (ß = .31, $p < .01$), but tenure (ß = -.0001, $p < .05$), usage intensity (ß = -.00003, $p < .1$), and age (ß = -.005, $p < .01$) all reduce this negative effect, in support of Hypotheses 1, 3, and 4. Interaction intensity (ß = -.03, $p > .1$) does not exert such a moderating effect, so Hypothesis 2 is not supported by the data. These results are consistent across different estimation techniques (probit model, maximum likelihood procedure, linear probability model). More generally, all the estimation techniques produce qualitatively similar results for all our subsequent analyses, though we note some variations, such that the price differences, tenure, and interaction intensity exert more pronounced effects in the probit model, as might be expected due to some differences in the estimation technique used by each model. We outline the explanation for these differences in Appendix 1.

We also note some influences independent of the price increase, such that tenure (ß = -.0003, $p < .01$), interaction intensity (ß = -.14, $p < .01$), the number of minutes spent talking (ß = -.00001, $p < .01$), age (ß = -.006, $p < .01$), a Western Hungarian location (ß = -.11, $p < .01$), city size (ß = .08, $p < .05$) and household size (ß = -.12, $p < .1$) all reduce the probability of customer defection after service elimination. Mobile data used (ß = .00001, $p < .05$) slightly increases customer defection, whereas switching barriers (ß = -.06, $p > .1$) and satisfaction (ß = .07, $p > .1$) reveal no significant effects.

In the subsets, we further observe that for B2C (ß = .38, $p < .05$) and voice only (ß = .48, $p < .05$) segments, the price increase effect is stronger, whereas it is non-significant for B2B customers (ß = .04, $p > .1$). The moderating effects of tenure, interaction intensity, voice usage, and data usage with the price increase are not significant; however, age has stronger effects for both B2C (ß = -.08, $p < .01$) and voice only (ß = -.01, $p < .01$) segments.

Among the covariates, for tenure and interaction intensity, all main effects on customer defection remain the same across segments. Switching barriers becomes significant for B2B (ß = -.23, $p < .05$) and voice only (ß = -.40, $p < .05$), so a two-year contract reduces customer defection for these user groups. Age is significant for the voice and data users (ß = .01, $p < .1$). The influence of a Western Hungarian location is similar to that in the main model, except for voice only subscribers (ß = -.10, $p > .1$). A smaller city location increases the probability of staying with the service provider in the B2C segment (ß = .10, $p < .05$), as do bigger households for both B2C (ß = -.14, $p < .1$) and voice only (ß = -.13, $p < .05$) segments.

It should be noted that generally all used estimation techniques show qualitative very similar results (probit model, maximum likelihood procedure and linear probability model). Especially the two-step estimator and the maximum likelihood estimator hardly differ. There are some differences with the linear probability model (LPM). Especially price differences, tenure and interaction intensity show a more pronounced effect in the probit model than in the LPM. However, such differences are expected as explained in Appendix 1.

Now we move to our second research question, related to changes in customer behavior in the post-elimination phase. In the second-stage equation, we investigate the effect of service elimination on usage behavior (Table 3) and find that a price increase (ß = .29, $p < .01$) is associated with higher levels of post-elimination usage intensity, as we predicted in Hypothesis 5. Interaction intensity (ß = -.02, $p < .05$) decreases post-elimination usage, in an unexpected and unpredicted significant effect, which suggests the need for further research. Moreover, the number of minutes spent talking (ß = .00001, p < .01) and data usage (ß = .00003, p < .01) increase, whereas larger cities (ß = -.19, p < .01) decrease, post-elimination usage significantly. No other covariates (age, satisfaction, regional location, and household size) exert significant effects, though regional location and household size are significant in the ordinary least square (OLS) analyses.

In the other models we tested besides the base model (B2C, B2B, voice only and voice and data), the effects of a price increase do not significantly change, and interaction intensity effects are similar to the main model, except that for B2B and voice and data subscribers, this effect is not significant. With respect to the covariates, voice usage intensity has the same effect across all groups; data usage intensity has no effect on the voice only users, of course. Satisfaction is significant for B2C (ß = .05, p < .1) and voice only (ß = .06, p < .05) customers. Subscribers living in smaller cities exhibit lower usage intensity following elimination if they are B2C (ß = -.13, p < .1) and voice only (ß = -.19, p < .5) customers.

Simple OLS estimates do not account for a possible sample selection problem, as occurs when the remaining sample, after service elimination, is not random with respect to the second-stage variables. The Heckman maximum likelihood estimator accounts for a possible selection bias (see Appendix 1), so in Tables 2 and 3, we provide the maximum likelihood results. The highly significant coefficient for the inverse Mills ratio (Table 3) for the basic model signals the presence of substantial selection bias; that is, some unobserved factors influence both the first- and second-stage decisions. When we estimate the model with the two-step estimator and simple OLS, the results are not notably different.[7] Therefore, we calculate an average truncation effect (see details for explanation in Appendix 1) to determine how much the usage intensity difference shifts due to

[7] The results of the two-step estimator and OLS are available on request.

the sample selection bias. The average inverse Mills ratio[8] is .335, so the truncation effect ($\lambda \times$ average inverse Mills value) is $.679 \times .335 = .23$. A customer with sample average characteristics, selected as churned, thus is likely to exhibit $[\exp(.23) - 1] \times 100 = 25.5\%$ higher usage than average customers with comparable characteristics who remain in the sample.

Churned customers thus typically may reveal higher usage intensity if they were observed in the second stage, implying a heavy user bias. That is, customers who exhibit higher phone usage typically have a higher propensity to churn during service elimination, whereas those with lower usage stay. Our Heckman two-step and maximum likelihood estimators deliver estimates based on the whole population, not just those who happens to remain in the sample, to correct for this bias. This correction represents the primary reason for choosing this methodology. Furthermore, we note several explanations for the heavy user bias. First, increased, more intense usage causes customers to become more conscious of the terms of the contract, and eliminating a service package that they had adopted means they have less reason to stay. The terms of the contract may be less known to light users, so changes in current conditions due to the service elimination might not cause them to leave.

Second, evidence of a sample selection bias also emerges from the estimate of the correlation between first- and second-stage residuals, which is .413 in the base model. Unobservable variables thus relate to decisions in both stages, with the same sign. Such exogenous variables might include brand image or psychological factors influencing usage and churn rates, There are many unobserved factors that might have an effect on why heavy users actually rather leave compared to light users: personality traits, such as risk-taking, or openness to change determine how one might react to an unexpected situation, like service elimination. These are areas for further research.

[8] In the Heckman procedure, the inverse Mills ratio corrects for the self-selection bias.

However, truncation bias seems only present in the B2C segment, not the B2B segment, which may be plausible, because psychological factors and brand image would affect the B2C segment more. This might be due principally to the individual decision-making process regarding service elimination: in a B2C segment the decision is usually made by one person, whose characteristics are more or less observable in the sample. In the case of a larger corporation however, the decision is made by a larger team, not an individual, thus larger usage intensity in relation with the heavy user bias does not have a significant effect for customer defection.

These statements regarding the presence of a sample selection bias rely on our identifying restrictions, according to which tenure and switching barriers have no role in the second-stage decision. Without this restriction, the sign of the estimated parameter for the inverse Mills ratio is still positive but not statistically significant. In this case, identification of a sample selection effect solely relies on the non-linearity of the inverse Mills ratio. But this non-linearity is weak for the bulk of the observations; in the absence of additional identifying restrictions, the inverse Mills ratio is nearly a linear combination of all the variables in the second stage, leading to severe multicollinearity. Reasonable uses of the Heckman procedure thus require some additional identifying restrictions. Fortunately, none of our hypotheses depend on the identifying restrictions. The results from the Heckman procedure and simple OLS are similar; in particular, the price effect is nearly identical. Interaction intensity is highly significant in all versions but numerically less pronounced in the Heckman versions, as is the case for regional and household size effects.

4.5 Robustness analysis

To check the reliability of results, we rely on a double robustness procedure (Carpenter et al. 2006), based on the idea that the model should be estimated for three data sets: all available data (with the imputed price increase data), partially observed data (without the imputed price variable), and the probability of observed data. Because we obtained a firm's actual data set, this third set is not applicable. As explained in Section 4.3. for the basic model, one variable (price increase) had to be imputed due to data quality issues. To check the robustness of this imputation, we excluded the imputed price increase variable and its interactions, so that we conduct the analyses only with full data entries (Variant 2), as summarized in Tables 4 and 5. When we thus exclude the logarithm of old and new monthly fee differences (price increase), the coefficients of the other variables do not change remarkably relative to the original model. Thus, we do not find evidence of contamination by the imputation procedure. We also test the model when we restrict the analysis to only significant variables (Variant 3). Again, most of the coefficients do not change, though the significance of regional location changes slightly. The basic model includes non-significant variables related to extant literature, including switching barrier.

To ensure the robustness of the customer defection prediction, we also examine several measures of out-of-sample fit. When we order the sample randomly, we can estimate the models for the first 75% of observations. With these estimates, we then predict the remaining 25% of observations and calculate the correlation of actual to predicted values (in a usual regression setting, it corresponds to the square root of R^2). This measure of fit should not differ much across out-of-sample, in-sample, or full-sample values. For the first-stage model, the in-sample correlation of predicted to actual values for churn is .29, that for the out-of-sample is .31, and the correlation for the full sample is .30. These similar values do not give rise to concerns. The hit rates for the first stage (percentage of correctly classifying churn or not) are .81, .81, and .8 for full-sample, in-sample, and out-sample model estimates. For the other model variants (B2C, B2C, voice only and voice and data), they range from .7 to –.92, but more importantly, they do not differ notably across the in- and out-of-sample estimates. Although the hit rates of our first stage models are comparatively high, classifying customers who stay generally is more accurate than classifying those who leave. This is not unusual for data with a very unevean divisions of stays and leaves and due to the common but arbitrary chosen threshold value of .5 for mapping the latent variable to the actual outcome.

For the first-stage estimations, we apply a Hosmer-Lemeshow specification test to evaluate the goodness of fit. For this check, the sample is not ordered randomly but rather according to the predicted probabilities to stay. The sample is divided into subgroups based on segment criteria, four in our case, and then we compare the average predicted probabilities to stay against the sample frequency of staying for all subgroups. The ratio of these two measures should not differ across subgroups. The base model and B2B model pass this test, but for the voice and data model, the test also suggests severe specification problems, so we removed this segment from the results.

For the second-stage model, we compare the correlations of actual versus predicted usage differences after service elimination among non-churned customers, and we obtain values of .25, .24 and .24 for the full-sample, in-sample, and out-of-sample cases. The correlations remain similar for all other model variants. Therefore, the comparisons of in-sample and out-of-sample fit do not indicate misspecifications. The only caveats are the results of the Hosmer-Lemeshow test for first-stage variants of the B2C and voice only models. The results from these model variants thus require additional caution, though the in- and out-of-sample fits are acceptable for these variants as well.

4.6 Discussion

To identify factors that might reduce the risk of customer defection following a price increase due to service elimination, as well as post-elimination behavior we seek to reveal the effects of service elimination on customers. We use Heckman sample selection to define high and low churn moderators. The resulting model shows that tenure, usage intensity, and age significantly reduce the risk of customer defection. Among non-churned customers, and in line with a priori expectations, higher prices and less intense interactions encourage greater usage intensity after the service elimination project. To the best of our knowledge, these effects have not been investigated previously.

By estimating the probability of customer defection, as a success measure, we shed light on how service firms can mitigate customer defection following a service elimination project, then further influence customer behaviors afterward, answering our third research question related to firm strategies ensuring the success of service elimination. Specifically, if service providers decide strategically to eliminate some services, they need to consider the impacts on customers. New, younger customers and light users are endangered groups, in terms of customer defection, and service firms also should take steps to optimize the level of interaction with customers before and during the service elimination process.

5. STUDY 2

Study 1 provides implications for loyal customers but not for customers who defect. With an experimental design, we can incorporate both customer groups, to determine how service usage following service elimination might change, depending on customer status (loyal or defected); we also consider the impacts of competition. Here, we do not investigate why customers switch or remain loyal; instead, we rather look at the consequences of those decisions. Also in contrast with Study 1, in which the service elimination could lead to higher or lower prices, in Study 2 we address the consequences of a price increase, which creates a disadvantaged inequality situation (Xia, Monroe, & Cox, 2004), higher perceived unfairness, and thus perhaps more explicit responses from customers.

In prior research dedicated to understanding the reasons for switching behavior, several theoretical models explain whether a customer decides to switch (Carter, Gray, D'Alessandro, & Johnson, 2016) but not their behaviors after this decision. The distinction between loyal customers and defectors might reflect consumer inertia (Han, Kim, & Kim, 2011; Lee & Neale, 2012). Consumers with high levels of inertia are less likely to change service providers, even if they are dissatisfied, which also might stem from their confusion about available alternatives or lack of trust in other service providers (Turnbull, Leek, & Ying, 2000). With the prediction that inertia leads the customer to remain loyal, despite the price increase due to a service elimination, we also anticipate ongoing effects of inertia. That is, even if the customer increases her or his usage intensity to compensate for increased inputs (i.e., price paid) and thus restore fairness or balance perceptions, inertia may limit those increases. In contrast, defected customers might persist in their proactive behaviors and increase their usage intensity, especially if they obtain a better price by switching. Such effects would have economic rationales but also could stem fro the excitement of using a new service. Altogether, we expect defected customers to use the service more intensively than loyal customers.

Hypothesis 6: Post-elimination service usage intensity will be higher for defected customers than for loyal customers following a price-increase

The presence of competitive offerings and customer's awareness of those offerings also may evoke behavioral changes, especially if the service elimination leads to higher prices. To establish this prediction, we turn to selective hypothesis theory, according to which people faced with uncertain conditions simplify their information search behavior and focus on a single hypothesis, which they test using some relevant criterion. If this criterion is met, the hypothesis is good enough, and people terminate their search process. Otherwise, they craft a new hypothesis and restart the process (Cronley, Posavac, Meyer, Kardes, & Kellaris, 2005). Such selective hypothesis testing helps people decrease the efforts and time required to identify and assess viable options (Sanbonmatsu, Posavac, Kardes, & Mantel, 1998). For our study, a customer who is not subject to competitive effects might not engage in cognitive work and thus will be less motivated to change usage behavior. But when competitive effects arise, customers will become aware of competitive offerings and might adjust their behavior to this new information.

Hypothesis 7: Post-elimination service usage intensity will be higher in the presence of competitive effects (involving both different and similar competitive offerings) compared to the absence of competitive effects following a price increase

5.1 Design and procedure

In our conceptualization, competitive effects take three different forms: an absence of competitive effects, such that the customer is not aware of competitive offerings; competitive effects with differences in competitive offerings, so customers compare competitive offerings and finds considerable differences; or competitive effects without differences, such that the comparison takes place but reveals no significant differences. Therefore the experimental design is a 2*3 between subject factorial design based on service scenarios in which we manipulated competitive effects (none, competitive effects without differences, competitive effects with differences) and the status of customer (loyal and defected). Table 6 presents the description of the scenarios.

We adapted the measures from Wirtz et al. (2017) for measuring voice and data usage intensity. The scale includes the item “In the situation you were considering, how likely would you make more phone calls in the future?” for voice usage intensity, and “In the situation you were considering, how likely would you increase your Internet use on your mobile in the future?” for data usage intensity, all rated on a 5-point scale from “extremely unlikely” to “extremely likely”.

Study 2 participants were members of the MTurk online panel, who received a nominal fee. They were randomly assigned to one condition in the 2 (customer status: loyal vs. defected) × 3 (competition: none vs. competitive effects without differences vs. competitive effects with differences) between-subjects factorial design, in which intention to increase post-elimination voice and data usage and satisfaction were the dependent variables. They read descriptions about the service elimination situation, which contained our manipulations, as detailed in Table 6. The price increase (15%) was the same in all scenarios; customer status and competition effect levels were randomized. To encourage comprehension, participants had to stay on the same page for 90 seconds before moving to the next section. We included two "blue dot" instructional manipulation checks (Oppenheimer, Meyvis, & Davidenko, 2009) to ensure they read the questions carefully (e.g., "On this particular question, select strongly agree").

After reading the scenario, participants completed direct measures of their intentions to increase post-elimination data and voice usage intensity. We adapted measures from Wirtz, Gottel, and Daiser (2017) for voice and data usage intensity, such as "In the situation you were considering, how likely would you make more phone calls in the future?" or "In the situation you were considering, how likely would you increase your Internet use on your mobile in the future?" The 5-point scales ranged from "extremely unlikely" to "extremely likely." We also included items to test for the perceived reality of the scenario. Finally, we collected demographic information and debriefed the participants.

5.2 Results

Although 616 participants submitted responses, we removed those respondents who failed the instructional manipulation checks, leaving a final sample size of 553 participants (M_{Age} = 38.6 years, 36.8% women). The manipulations of customer defection (loyal vs. defected) and competition (none vs. competitive offerings without differences vs. competitive offerings with differences) produced the intended results (Table 7). The results show that participants in the defected condition significantly increased their post-elimination data usage intensity (M_{loyal} = 3.12, $M_{defected}$ = 3.36, $F(1,548) = 6.20$, $p < .02$) compared with those in the loyal condition, in response to the price increase. We thus find support for Hypothesis 7. Furthermore, participants in the noncompetitive condition increased their post-elimination voice usage intensity significantly less (M_{none} = 3.07, $M_{without\ differences}$ = 3.26, $M_{with\ differences}$ = 3.36, $F(2,548) = 2.98$, $p < .06$) than those in both competitive conditions (Figure 4), in support of Hypothesis 8. According to the Bonferroni post hoc test, the difference between *none* and *with differences* conditions is significant.

The two-way interaction of customer defection and competition does not exert a significant effect on post-elimination usage intensity.

5.3 Discussion

The results of Study 2 support our predictions: respondents increase their post-elimination data usage intensity after leaving the service provider. Different levels of competition exert similar effects on post-elimination voice usage intensity. With this evidence, we build on our Study 1 findings by revealing how customer defection increases post-elimination usage intensity. For customers in a state of inertia, who remain loyal, their usage behavior also increases only moderately, whereas more proactive, defected customers increase their usage behavior more after they switch.

We argue that those who leave may be more informed about service packages, because before they make the decision to leave, they likely collect additional information about the costs of breaking their existing contract, signing fees with another service provider, and the service packages available. They also might experiment more with the new service.

This outcome is similar to the effect of price increase on post-elimination usage intensity, because we observe that intensified post-elimination usage is a consequence of an overcompensation for price increases. We assume that this behavior is associated with greater consciousness of the exact terms and conditions of the service packages. Across these two studies, we thus conclude that an increase in post-elimination usage intensity is due to a price increase but also is associated with customer defection, especially in more competitive markets. In line with the selective hypothesis testing theory (Sanbonmatsu et al., 1998), it appears that following a service elimination in a competitive market, customers gain awareness of the existence of competitive offerings and try to adjust their behavior to the new circumstances. Finally, we capture an interesting aspect of competition, in that we manipulate its levels and thus capture customer perceptions of competition. Incorporating real competitive data could yield further relevant results.

6. GENERAL DISCUSSION

6.1 The risk of service elimination defection reduces with tenure, usage intensity and age during a price increase

Three defection indicators related to a price increase due to service elimination emerge from our findings: tenure, usage intensity, and age. These findings align with findings in prior literature regarding normal customer retention cases (Neslin, Gupta, Kamakura, Lu, & Mason, 2006) (without service elimination). First, longer relationships tend to be more stable, so customers defect only rarely. These stronger bonds with the service provider even prevent customers from leaving following a price increase. A service elimination is an unexpected situation, which may confuse consumers, but those with longer tenures do not seem to react as negatively to price increases due to the elimination. Therefore, companies should focus particularly on new customers in a service elimination process, which represent are an endangered group in terms of customer defection.

Second, data usage intensity reduces the risk of customer defection, in accordance with the heavy user bias. Heavy users tend to stay more with the service provider, and they are less sensitive to price changes.

Third, the statistically significant interaction variable between price increase and age signals that age reduces the churn resulting from a price increase. Older customers are more likely to remain.

We also observe, across different segments, that the effect of a price increase on customer defection is significant among B2C and voice only segments, without any effect for B2B segments. This result might reflect the B2B decision-making process, for which decision-makers tend to be different from users. Thus, a service elimination situation might have a greater effect in B2C settings, in which the subscriber and user usually are the same.

6.2 Price increase raises post-elimination usage intensity

The second-stage results reveal that customers who decide to remain with the company following the service elimination, despite the price increase, increase their usage intensity. We suggest a number of plausible explantions for this outcome. First, due to increased interaction intensity during service elimination, customers may become better informed about service conditions in general, and increase usage to make better use of them. Interaction intensity in general increases the probability of the customer staying, so we can argue that customers who receive more contact from the service company before service elimination are more likely to remain. In the second stage, we only observe customers who remain, which means that they probably had more contact with the service firm than those who left according to company practice. More contact means more detailed information about possible new service packages, service package conditions, deadlines, and so on.

Second, more intensive contact often results in a more conscious choice regarding the service package after service elimination. Often, service providers experience that customers barely know their monthly fee. The name and accurate conditions of the service package are even harder to remember. Considering these average customer perceptions of service subscriptions, more intense contact with the provider might increase their knowledge and change their attitude affecting customer defection decisions. When choosing a new service package, these more conscious customers might realize that they are paying more for something that is actually valuable to them.

Especially in telecommunications, consumers often focus on value for the money, not the absolute price of the service package. If they are heavy users, a flat rate would be the best choice, because a price-per-minute fee likely would be higher. Accordingly, we argue that greater customer consciousness, generated by the price increase due to service elimination, might increase usage intensity, because customers become better informed about what they are actually paying for. Their understanding of the exact conditions of the service package changes their behavior, pointing to the importance of pre-elimination interactions.

6.3 Theoretical contributions

Previous empirical work has examined decision-making and processes associated with service elimination projects, rather than their effects on customer defection (Avlonitis & Argouslidis, 2012). By offering insights for how to enhance the success of service elimination processes, we establish three main contributions. First, analyzing post-elimination phases from customers' perspective can inform service elimination literature. Success factors in the area of service elimination were only examined in financial or multi-sector studies (Gounaris et al., 2006); on the other hand, the performance outcome was assessed in manufacturing sectors only (Avlonitis & Argouslidis, 2012). Our study fills an important gap in service elimination literature by focusing on customers' perspective.

Second, this study identifies some main success indicators, namely, tenure, usage intensity, and age, which reduce the risk of customer defection in response to a price increase due to service elimination. The consumer groups most threatened by service elimination processes, in terms of customer defection, are new, younger customers and light users. Although the direct effects of tenure, interaction intensity, usage intensity, and age in reducing general churn intentions have been established, we also go a step further by outlining their moderating effects, in conjunction with a price increase. Moreover, our findings help clarify some divergent findings with regard to usage intensity and interaction intensity, which might arise because the service life cycle determines the need for interaction intensity. The introduction and elimination phases of a service may require a more intense interaction; during other phases, customers do not necessarily need such intensity. The Study 1 results suggest that the elimination phase requires more intense interactions between the service provider and the customer. We also find that a price increase can intensify subsequent usage, which represents a contribution for a less studied topic area.

Third, service elimination may be essential for service portfolio innovation and management, in the sense that service innovation and service elimination are both part of service range management efforts (Argouslidis, 2004). Although less frequently investigate, the elimination of existing services can help accelerate service innovation.

6.4 Managerial implications

This research has practical implications as well, regarding the implementation of insights obtained through customer reactions into a service elimination strategy. In particular, decision-makers should leverage these findings to reduce the risk of customer defection during service elimination, by ensuring the appropriate pricing of the new offer, because low switching costs will encourage customers to accept better alternatives. Even if a price increase is unavoidable, the negative effects on customer defection can be avoided by targeting younger, new, and light users with unique service elimination propositions. These customers are the most at risk of defecting in response to a price increase, but older customers have a higher probability of remaining.

In turn, the effect of a price increase in intensifying usage after service elimination highlights the price–value aspect of customer expectations, instead of lower prices. Customers staying with the service provider following service elimination are engaging in a more intense usage behavior even though they are paying more compared to the pre-elimination period. If the customer receives a higher value service package, the price increase does not necessarily increase the probability of churn.

This more intense usage can be favorable for the service provider, as the additional network costs are marginal, but customer engagement can be higher, which might have an effect on cross-selling or service upgrades. Heavy users might be interested in other service propositions or new services as well.

6.5 Limitations and further research

These studies have some limitations. First, if a price increase is reflected in total spending by the customer, instead of monthly fee changes, it might have different effects. For example, calculating the total spending of the customer might reveal different aspects, such as the ratio of on-net or off-net charges (differences between using the same or other competitive networks); or the ratio of out-of-bundle and in-bundle usage (how high is the proportion of usage not covered by the monthly fee). So different conclusions could be reached by incorporating all the variable costs, going beyond the monthly fee. This in turncould help to better understandthe effects of a price increase on customer churn in case of service elimination. For instance, price increase in itself could have a less prominent effect on customer defection if out-of-bundle usage is higher than the monthly fee. Of course, this might signal the result of a non-optimal service package choice, but still, the effect of increasing the monthly fee should not be that strong in this case. Gathering total spending would require a closer collaboration with the service provider, but such data collection efforts are challenging, because different information tends to be stored in different databases or formats.

Second, switching barriers might be significant if all costs related to switching could be included. This might refer to every possible costs related to a switching for the customer, such as information, searching, transaction, learning costs, loyalty discounts, costs related to a cognitive effort, costs associated with the financial, social and psychological risks (Fornell, 1992).

Third, confirming whether the analysis outcomes are representative of the whole industry would require analyzing the databases of other service companies. Also, evidence from other key service areas might be required to strengthen the generalizability aspects, such as banking, and insurance, where we expect similar results. Finally, competitive service providers may react to the focal firm'spolicy by offering alternative or additional packages, and this might change the risk of customer defection. Further research might address the relationship between service elimination and customer defection through the consideration of these oligopoly effects.

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Appendix

Figure 1: Hypothesized effects between variables

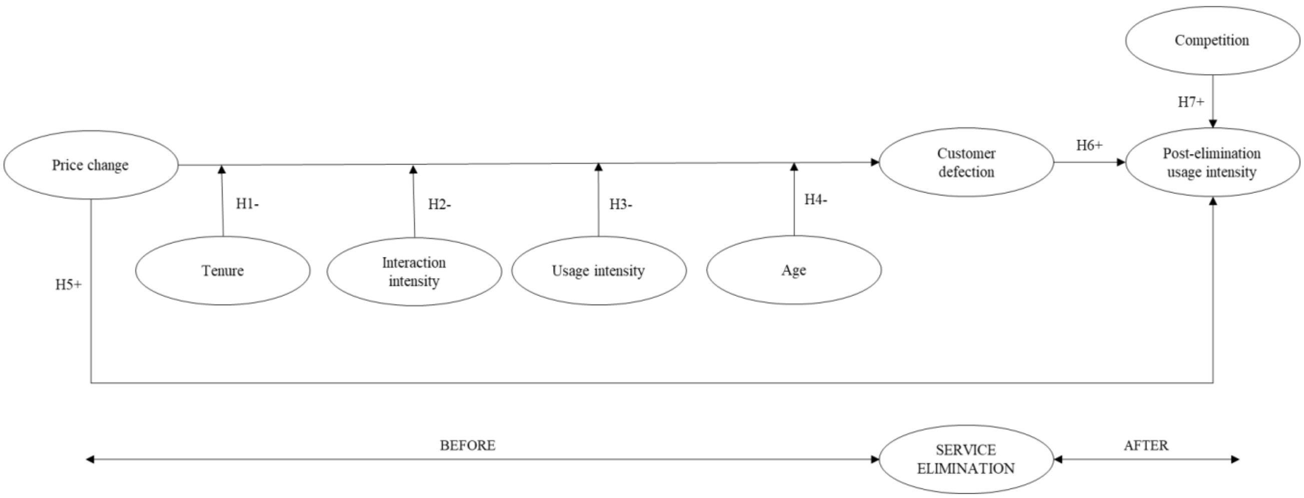

Figure 2: Interactions of price increase with tenure, age, and usage intensity (Study 1)

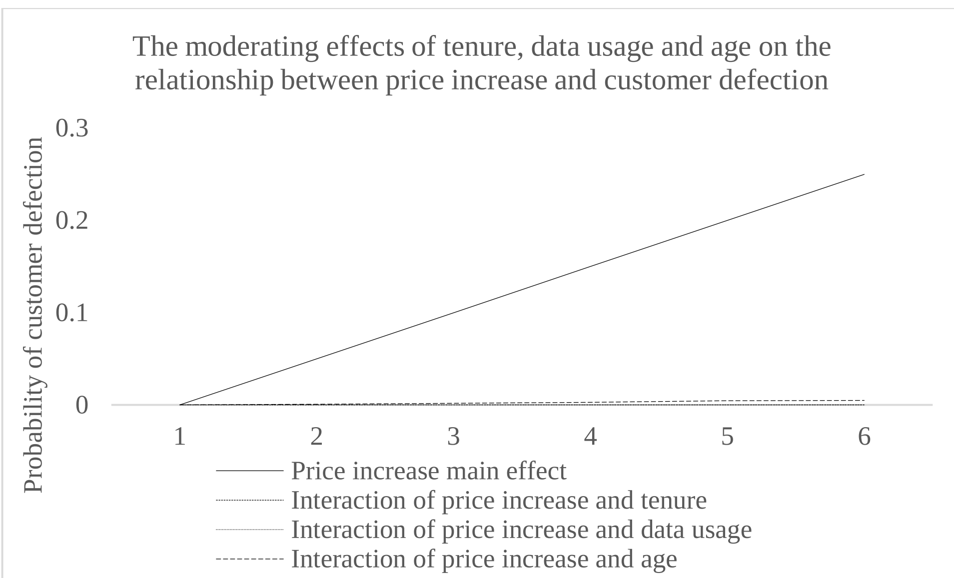

Table 1: Variables in the Heckman sample selection model (Study 1)

Variable type	Variable name	Description
Criterion variables	Customer defection	Defection is an operational measurement of customer retention, which takes a value of 1 if the customer changed service providers and 0 otherwise (first stage).
	Usage intensity difference	Difference in minutes customers talked, before and after elimination (second stage).
Independent variable	Price change	Logarithm of the difference between new and old monthly fee. Price increases in 45% of the cases and price decreases in 55% of the cases, which can be considered as a balanced sample.
Main effects	Tenure	Time elapsed between the start and end date of the contract, in days. The tenure range in the study is 3274 days (8.96 years).
	Interaction intensity	Number of calls initiated/received by the call center from the start of the customer's contract.
	Interaction intensity	Dummy variable, equal to 1 if data are available, and 0 otherwise.
	Voice usage intensity before elimination	Number of minutes the customer talked before the elimination (in minutes).
	Data usage intensity before elimination	Data the customer used before the elimination (in MBs).
	Age	Age of the customer, measured in years.
	Age dummy	Dummy variable equal to 1 if age data are available, and 0 otherwise.
	Switching barrier	Whether the two-year loyalty period with the service provider has passed (telecommunication service providers have a contract requirement of two years in Hungary). The dummy variable equals 1 if the customer is under a contract at the time of the elimination and 0 if out of contract.
	Caller satisfaction	Net Promoter Score given by the customer after a call center call (caller satisfaction). It is not directly related to overall satisfaction with the service, so we only use it as a covariate that might influence price change and churn.
	Caller satisfaction dummy	Dummy equal to 1 if satisfaction data are available, and 0 otherwise.
	Regional location	Dummy variable equal to 1 if the customer's city of residence is in Western Hungary, based on location of the country, and 0 otherwise.
	Size of city location	Similarly to Western Hungarian location, bigger cities also might have a greater variety of competitor offers that influences churn rates. Dummy variable equal to 1 if the customer's city of residence is a county seat in Hungary and 0 otherwise.
	Interaction of price increase and size of city location	Moderating effects of size of city location on price increase
	Household size	Bigger families with more household member may be less sensitive to service elimination effects. The number of members in the customer's household is a covariate.
	Household size dummy	Dummy variable equal to 1 if household size data are available, and 0 otherwise.

Table 2: First-stage regression results: Estimation of probabilities for churn during service elimination (Study 1)

	Dependent variable: Customer defection			
	Base model	B2C	B2B	Voice only
Main effect				
Price increase	0.30878***	0.37672**	0.03462	0.47644**
	(0.09203)	(0.16251)	(0.12115)	(0.19503)
Interaction of price increase and tenure	-0.00013**	-0.00007	-0.0001	-0.00007
	(0.00006)	(0.00007)	(0.0001)	(0.00008)
Interaction of price increase and interaction intensity	-0.02623	-0.03947	0.01911	0.00673
	(0.02477)	(0.03859)	(0.02114)	(0.03437)
Interaction of price increase and voice usage	<0.000001	<0.000001	0.00001	<0.000001
	(0.00000)	(0.00000)	(0.00001)	(0.00000)
Interaction of price increase and data usage	-0.00003*	-0.00002	-0.00013	-0.00004
	(0.00001)	(0.00002)	(0.00041)	(0.00006)
Interaction of price increase and age	-0.00491***	-0.00836***	0.00053	-0.01193***
	(0.00157)	(0.0029)	(0.00173)	(0.00383)
Control variables				
Tenure	-0.00027***	-0.00021***	-0.00028**	0.00014*
	(0.00006)	(0.00007)	(0.00012)	(0.00008)
Interaction intensity	-0.14392***	-0.18443***	-0.08877**	-0.11152**
	(0.02463)	(0.03551)	(0.03462)	(0.04336)
Interaction intensity dummy	0.29128***	0.22099**	0.25814**	0.05123
	(0.07525)	(0.1022)	(0.1217)	(0.13407)
Voice usage intensity	-0.00001***	-0.00001***	-0.00003**	<0.000001
	(0.00000)	(0.00000)	(0.00001)	(0.00000)
Data usage intensity	0.00001**	<0.000001	-0.00009	-0.00004
	(0.00000)	(0.00000)	(0.00041)	(0.00005)
Age	-0.00557***	-0.00312	-0.00091	0.00049
	(0.00183)	(0.00215)	(0.00371)	(0.00493)
Age dummy	-0.65668***	-0.65343***	0.23405	0.11056
	(0.08995)	(0.10735)	(0.20529)	(0.26254)
Switching barrier	-0.05926	0.03148	-0.23089**	-0.40097**
	(0.06297)	(0.07771)	(0.11601)	(0.18091)
Satisfaction	0.06553	0.09917	0.00101	0.03122
	(0.05053)	(0.06067)	(0.09382)	(0.05368)
Satisfaction dummy	0.81022**	1.01410**	0.45214	0.45037
	(0.40949)	(0.49636)	(0.70819)	(0.44774)
Regional location (Eastern or Western Hungary)	-0.11006***	-0.12922***	-0.15641**	-0.10162
	(0.03984)	(0.04769)	(0.0795)	(0.09157)
Size of city location	0.07872**	0.10160**	-0.00976	0.11212

	(0.03638)	(0.04309)	(0.07457)	(0.08911)
Household size	-0.12306*	-0.14024*	-0.04903	-0.13763**
	(0.06446)	(0.07415)	(0.15001)	(0.06947)
Household size dummy	0.29211	0.29537	0.18733	-0.11226
	(0.20725)	(0.23693)	(0.48249)	(0.2367)
Moderator				
Interaction of price increase and size of city location	0.02331	0.0158	-0.02144	0.03174
	(0.06557)	(0.08415)	(0.09867)	(0.11504)
Constant	-1.33330***	-1.52673***	-1.59592*	-1.61602***
	(0.47452)	(0.57019)	(0.87088)	(0.57665)
In-sample correlation of actual vs. predicted for churn	0.2961	0.3237	0.2083	0.2322
Out-of-sample correlation of actual vs. predicted for churn	0.3100	0.3188	0.1934	0.1471
Full sample correlation of actual vs. predicted for churn	0.3011	0.3229	0.2125	0.2214
In-sample hit rate	0.8063	0.7645	0.8984	0.9239
Out-of-sample hit rate	0.8024	0.7727	0.8847	0.9072
Correctly classified	80.54%	76.59%	89.51%	92.04%
Hosmer-Lemeshow goodness-of-fit chi-square(1)	0.66	5.01	0.86	5.51
Prob > chi-square	0.4172	0.0252	0.3527	0.0189
Observations	7668	5390	2278	2161

$*p < .1$; $**p < .05$; $***p < .01$.

Table 3: Second-stage regression results: Estimation of usage differences during service elimination by non-churned customers (Study 1)

	Dependent variable: Usage intensity difference			
	Base model	B2C	B2B	Voice only
Main effect				
Price increase	0.28647***	0.24072***	0.40706***	0.30549***
	(0.04284)	(0.05246)	(0.07517)	(0.06998)
Interaction intensity	-0.01986**	-0.01978**	-0.01416	-0.02869***
	(0.00851)	(0.00964)	(0.01958)	(0.01062)
Interaction intensity dummy	-0.0006	0.01068	0.05671	0.20168**
	(0.07458)	(0.12651)	(0.0941)	(0.09053)
Control variables				
Voice usage intensity	0.00001***	0.00001***	0.00001***	0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Data usage intensity	0.00003***	0.00003***	0.00010***	0.00002
	(0.00000)	(0.00000)	(0.00003)	(0.00003)
Age	0.00306	0.00318	0.00226	0.00665
	(0.00223)	(0.00301)	(0.00313)	(0.00406)
Age dummy	0.39494***	0.45415**	0.28644	0.69238***
	(0.12423)	(0.17655)	(0.17501)	(0.20063)
Satisfaction	0.01286	0.05194*	-0.03067	0.06246**
	(0.02243)	(0.02659)	(0.03646)	(0.02969)
Satisfaction dummy	0.29043*	0.35924*	0.26673	0.50450**
	(0.15552)	(0.19905)	(0.24452)	(0.22341)
Regional location (Eastern or Western Hungary)	-0.07649	-0.12808*	0.001	-0.19340**
	(0.04962)	(0.06788)	(0.0763)	(0.08578)
Size of city location	-0.18500***	-0.19787***	-0.16647**	-0.03945
	(-0.04508)	(0.0589)	(0.07144)	(0.08049)
Household size	0.02878	0.06446	-0.08491	0.00616
	(0.05561)	(0.06406)	(0.11964)	(0.06631)
Household size dummy	0.24713	0.38426*	-0.17082	0.38894*
	(0.18612)	(0.22796)	(0.34669)	(0.2336)
Constant	-1.60771***	-1.83029***	-1.02975**	-1.86857***
	(0.27144)	(0.34113)	(0.43771)	(0.39109)
Lambda	0.6239778**	.6921685**	-.0184888	-0.7222568**
	(0.2054606)	(0.3880799)	(0.162614)	(0.2702847)
Average inverse Mills ratio	0.3349124	0.3917482	0.1968205	0.1535714
In-sample correlation of actual vs. predicted for usage difference	0.2420	0.2701	0.2146	0.2607
Out-of-sample correlation of actual vs. predicted for usage difference	0.2435	0.2617	0.1570	0.2389
Full sample correlation of actual vs. predicted for usage difference	0.2506	0.2442	0.2491	0.2369
Observations	7668	5390	2278	2161

*$p < .1$; **$p < .05$; ***$p < .01$.

Table 4: Robustness analysis for first-stage regression results: Estimation of probabilities for churn during service elimination (Study 1)

	Dependent variable: Customer defection		
	Basis model	Variant 2	Variant 3
Main effect			
Price increase	0.30878***		0.41725***
	(0.09203)		-0.08239
Interaction of price increase and tenure	-0.00013**		-0.00016**
	(0.00006)		-0.00007
Interaction of price increase and interaction intensity	-0.02623		
	(0.02477)		
Interaction of price increase and voice usage	0.000000		
	(0.00000)		
Interaction of price increase and data usage	-0.00003*		-0.00003***
	(0.00001)		-0.00001
Interaction of price increase and age	-0.00491***		-0.00657***
	(0.00157)		-0.00169
Control variables			
Tenure	-0.00027***	-0.00027***	-0.00022***
	(0.00006)	-0.00004	-0.00003
Interaction intensity	-0.14392***	-0.13062***	-0.15620***
	(0.02463)	-0.02652	-0.02763
Interaction intensity dummy	0.29128***	0.28042***	0.31820***
	(0.07525)	-0.07592	-0.07825
Voice usage intensity	-0.00001***	-0.00001***	-0.00001***
	(0.00000)	(0.00000)	(0.00000)
Data usage intensity	0.00001**	0.00001**	0.00001**
	(0.00000)	(0.00000)	(0.00000)
Age	-0.00557***	-0.00743***	-0.00581***
	(0.00183)	-0.00179	-0.00183
Age dummy	-0.65668***	-0.71450***	-0.65844***
	(0.08995)	-0.08739	-0.08977
Switching barrier	-0.05926	-0.08139	
	(0.06297)	-0.0535	
Satisfaction	0.06553	0.06139	
	(0.05053)	-0.04322	
Satisfaction dummy	0.81022**	0.80920**	
	(0.40949)	-0.34942	
Regional location (Eastern or Western Hungary)	-0.11006***	-0.05913	-0.10767***
	(0.03984)	-0.03779	-0.03943
Size of city location	0.07872**	0.09479***	0.08510**
	(0.03638)	-0.03456	-0.03617
Household size	-0.12306*	-0.07626	-0.20854***
	(0.06446)	-0.06918	-0.02869

Household size dummy	0.29211	0.33471	
	(0.20725)	-0.22188	
Moderator			
Interaction of price increase and size of city location	0.02331		
	(0.06557)		
Constant	-1.33330***	-1.36688***	-0.32557***
	(0.47452)	-0.4377	-0.11714
In-sample correlation of actual vs. predicted for churn	0.2961	0.2754	0.3002
Out-of-sample correlation of actual vs. predicted for churn	0.3100	0.3038	0.2910
Full sample correlation of actual vs. predicted for churn	0.3011	0.2841	0.2967
In-sample hit rate	0.8063	0.8164	0.8048
Out-of-sample hit rate	0.8024	0.8158	0.8053
Correctly classified	80.54%	81.63%	80.56%
Hosmer-Lemeshow goodness-of-fit chi-square(1)	0.66	1.15	0.20
Prob > chi-square	0.4172	0.2828	0.6567
Observations	7668	8541	7673

*p < .1; **p < .05; ***p < .01.

Table 5: Robustness analysis for second-stage regression results: Estimation of usage differences during service elimination by non-churned customers (Study 1)

	Dependent variable: Usage intensity difference		
	Basis model	Variant 2	Variant 3
Main effect			
Price increase	-0.28647***		
	(0.04284)		
Interaction intensity	0.01986**	0.01229	0.03213***
	(0.00851)	(0.00859)	(0.00699)
Interaction intensity dummy	0.0006	0.14842*	
	(0.07458)	(0.0843)	
Control variables			
Voice usage intensity	-0.00001***	-0.00002***	-0.00001***
	(0.00000)	(0.00000)	(0.00000)
Data usage intensity	-0.00003***	-0.00003***	-0.00003***
	(0.00000)	(0.00001)	(0.00000)
Age	-0.00306	-0.00620**	
	(0.00223)	(0.00243)	
Age dummy	-0.39494***	-0.61112***	
	(0.12423)	(0.14267)	
Satisfaction	-0.01286	-0.00088	
	(0.02243)	(0.02612)	
Satisfaction dummy	-0.29043*	-0.13604	
	(0.15552)	(0.17524)	
Regional location (Eastern or Western Hungary)	0.07649	0.08765*	
	(0.04962)	(0.04929)	
Size of city location	0.18500***	0.19603***	0.14240***
	(-0.04508)	(0.04486)	(0.04174)
Household size	-0.02878	-0.04692	
	(0.05561)	(0.05898)	
Household size dummy	-0.24713	-0.13852	
	(0.18612)	(0.20258)	
Constant	1.60771***	1.69576***	0.89673***
	(0.27144)	(0.28907)	(0.06106)
Lambda	0.6239778**	1.470507**	0.6085228**
	(0.2054606)	(0.3271948)	(0.1532508)
Average inverse Mills ratio	0.3349124	.3195219	.3343699
In-sample correlation of actual vs. predicted for usage difference	0.2420	0.1507	0.2366
Out-of-sample correlation of actual vs. predicted for usage difference	0.2435	0.1263	0.2224
Full sample correlation of actual vs. predicted for usage difference	0.2506	0.1845	0.2285
Observations			

*$p < .1$; **$p < .05$; ***$p < .01$.

Table 6: Scenarios (Study 2)

Base scenario: introducing the service elimination situation	
All respondents	You have been a customer of a mobile carrier for more than 5 years, and overall you are satisfied with the quality of service. Imagine that your mobile carrier eliminates your service package, meaning that the conditions of your service package are not available anymore. The customer service representative offers you a new plan at a rate 15% higher than current rate. The deadline of cancelling your current plan is approaching soon, but the customer service representative does not provide sufficient information about the whole process to you.
Competitive effect manipulation	
None	You find the new price plan quite unreasonable, but you don't have an idea where to look for a better alternative.
Competitive effect without differences	You find the new price plan quite unreasonable, so you compare it with some competitors and find that there are no better alternatives.
Competitive effect with differences	You find the new price plan quite unreasonable, so you compare it with some competitors and find that there are better alternatives available. (Additional sentence in case of loyal 3 version: However, switching to another carrier seems complicated and time consuming.)
Status of the customer manipulation	
Loyal	After taking everything into consideration, you decide to stay with your current carrier and accept the new terms.
Defected	After taking everything into consideration, you decide to leave your current carrier.

Table 7: Results (Study 2)

		Service usage intensity (voice)
Competitive effect	Competition- No differences	3.07**
	Competition- Without differences	3.26
	Competition- With differences	3.36**
		Service usage intensity (data)
Customer defection effect	Loyal	3.12
	Defected	3.36

*$p < .1$; **$p < .05$; ***$p < .01$.

Appendix 1: Heckman sample selection procedure (Study 1)

In a first step, we examine the factors that determine the probabilities of customers staying with the company after the service elimination. It constitutes a churn analysis in a service elimination context. The dependent variable is a dummy variable (stay or leave), which implies that probit or logit regressions are appropriate methods. However, we also can use a simple linear regression model (linear probability model, or LPM) to produce predicted probabilities that might be negative or greater than 1, especially for customers with unusual characteristics (cf. an average individual). The comparison of the estimated effects of the LPM and the average effects of the probit model is interesting, especially if the estimated effects differ substantially, which would hint that the distribution assumption of the probit model is inappropriate.

In a second step, we estimate the factors that determine differences in usage intensity after service elimination. For this purpose, we again could apply linear regression analyses, but in this case, the problem is that after service elimination, the remaining sample is no longer random, and unobservable factors of these customers likely influence both the first-stage decision (stay or leave) and the second-stage usage intensity decision. A sample selection problem thus arises, so the ordinary estimated parameters would be valid only as a linear approximation for the particular subsample, not the overall population. We are interested in population effects. Empirically, we can test for sample selection effects by reviewing the residuals of the first- and second-stage regressions to determine if they are correlated (usually measured by the correlation coefficient ρ).

For our study, after the service elimination, we observe a subsample and no control group. As a result, some popular estimation procedures are not applicable, like the difference-in-differences estimator (Krueger & Card, 1994). Instrumental variable estimators (Arellano & Bover, 1995) do not help either, because we would need exogenous instruments that correlate with the unobserved factors. If we had such variables, we would have used them in the first place.

According to Heckman (1979), this sample selection issue can be seen as an omitted variables bias, which can be resolved by including another variable in the second-stage regression, namely, the inverse Mills ratio;[9]

$$IMR_i = \frac{\phi\,(z_i'\ \gamma)}{\Phi\,(z_i'\ \gamma)},$$

where z_i are factors determining the first-stage decision of individual i, γ are the associated parameters estimated in the first stage by a probit regression, φ is the density function of the standardized normal distribution, and Φ is the cumulated distribution function of the standard normal. In turn, IMR_i is the expectation of the error term of the second step equation, conditional that individual i is an element. Therefore, the Heckman procedure is as follows:

1. Estimate the first-step decision with a probit model.
2. Using the linear predicted values of this model, $z_i'\ \gamma$, estimate the inverse Mills ratio for every individual in the sample.
3. Use the inverse Mills ratio as an additional variable in the second-stage regression, which can now be consistently estimated by ordinary least squares if the error terms of both equations are jointly normal distributed.
4. Include all second-stage variables in the first-stage regression, along with some regressors in the first stage that are not included in the second stage. If the sets of regressors are identical in both stages, the model's identification only rests on the non-linearity of the inverse Mills ratio.

[9] Note that different definitions of the inverse Mills ratio are available, but they turn out to be equivalent.

5. Test whether the coefficient of the inverse Mills ratio, usually denoted λ, is significant. If it is, the residuals of both stage regressions are correlated, and a sample section problem exists to be addressed with this procedure.
6. The extent of the sample selection problem, also called the truncation effect, can be measured by the product of the average inverse Mills ratio with the corresponding estimated parameter λ.

This procedure also can be replaced by a more efficient maximum likelihood estimator, which estimates the first- and second-stage problems simultaneously (Nawata, 1994). We use both estimators to ensure more robustness against specification errors, especially regarding the joint normal distribution assumption.

Appendix 2. Scale items (Study 2)

The experiment in Study 2 included the following measures, in English, on 5-point Likert-type scales, with endpoints of "strongly disagree" and "strongly agree," unless otherwise noted.

Usage Intensity Intention (Wirtz et al., 2017)

- **Voice**: In the situation you were considering, how likely would you make more phone calls in the future? In the situation you were considering, how much would you change your weekly phone calls in the future?
- **Data**: In the situation you were considering, how likely would you increase your Internet use on your mobile in the future? In the situation you were considering, how much would you change your Internet use on your mobile in the future?

Satisfaction (Gustafsson et al., 2005). Three items averaged to create the final satisfaction intention scale:

- I am satisfied with my current service provider.

- The service provider exceeds my expectations.
- The service provider is close to my ideal service provider.

Service Encounter Satisfaction (Smith & Bolton, 1998)

- I am satisfied with the way how the service provider handled this service elimination.

Negative Word-of-Mouth Intentions (Blodgett et al., 1997). Three items averaged to create the final satisfaction intention scale:

- I would warn my friends and relatives not to be customers of this company.
- If this had happened to me I would complain to my friends and relatives about this company.
- If this had happened to me I would make sure to tell my friends and relatives not to be customer of this company.

Attention Filters

- In the situation you were considering, what kind of service subscription do you have?
- In the situation you were considering, the service you are using is still available.
- In the situation you were considering, the new conditions are better.
- In the situation you were considering, you left your service provider after the service elimination.

Instructional Manipulation Check (Oppenheimer et al., 2009).

- On this particular question, select strongly agree.