# Essays on decision making dynamics in politics and consumer choice 

Helene Lie Røhr

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by<br>Helene Lie Røhr

# A dissertation submitted to BI Norwegian Business School for the degree of PhD 

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## Helene Lie Røhr

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BI Norwegian Business School
N-0442 Oslo
Phone +4746410000
www.bi.no

To Per and Ida

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## Chapter 1

Introduction and summary

## 1 Introduction

Individuals' choices are the foundation in economics; an individual makes the choice that maximizes her utility. Doing nothing or maintaining a previous decision is also a choicethe status quo choice (Samuelson and Zeckhauser, 1988). To explain the mechanisms resulting in status quo behavior, research point at both frictions and preference biases. Search costs and switching costs are examples of frictions which may make the choice of maintaining the current state the utility-maximizing solution, even though it would not be so in a frictionless world. Additionally, there are numerous preference biases which may result in individuals preferring the status quo, including the default effect, loss aversion, the endowment effect, procrastination, framing, anchoring, the sunk cost fallacy, regret avoidance, omission bias, and cognitive dissonance. ${ }^{1}$ Preference biases tend to become more prominent in the presence of uncertainty, and most real world's problems are uncertain.

Status quo behavior is observed in settings that are relevant for this thesis. Looking first to the political realm, sitting politicians have an increased probability of remaining in their position, that is, they have an incumbency advantage. ${ }^{2}$ Evidence of the incumbency advantage in candidate-centered systems are extensive. This thesis shows that incumbency advantages in a party-centered system, stem from the incumbent candidates' improved list position in the next election. Hence, the parties execute status quo behavior in their nomination process.

Moving to the realm of consumer choice, numerous purchase decisions are either very similar or pure replications of past purchase decisions. However, research has shown evidence of consumer inertia ${ }^{3}$ implying that consumers replicate past choices, even when close substitutes are less expensive. The last two chapters of this thesis discuss consumer inertia in switching of mobile subscription. First, I discuss switching of subscriptions

[^0]within a telecom operator, and second, I discuss consumers' decision to leave their telecom operator. Consumers' switching behavior following unanticipated price changes, indicates that the market is influenced by consumer inertia.

## 2 Empirical methods: a quasi-experimental approach

In determining causal effects, the "gold standard" is randomized controlled experiments. However, there are numerous situations where true experiments cannot be conducted. Using a randomized controlled experiment can be un-ethical (random assigning political candidates to seats), ${ }^{4}$ or infeasible (measuring the effect for a company launching a new product). If we want to measure the impact of electing certain politicians or a mass market launch of a new product, we normally have to settle with the second best, namely quasi-experimental methods. In this dissertation I rely on two commonly used quasi-experimental approaches: the regression discontinuity (RD) design to study the incumbency advantage, and the difference-in-difference method (DiD) to study consumer inertia.

RD methods are applicable when there is a clear ranking of individuals, the ranking determines whether or not an individual is treated, and individuals who are ranked close to the threshold for treatment, do not in influence their exact rank and treatment. A typical application of the RD design is analyzing the outcomes of close elections comparing candidates barely winning to candidates barely losing. Here, we can assume that both candidates are comparable before the election, and that differences ex post are due to the election outcome. In marketing, RD design can be applicable if targeting of product offers are geographical segregated or based on previous purchase where consumers do not know the algorithm deciding their product offering, cf. Hartmann, Nair and Narayanan (2011).

In the basic set up of a DiD estimation, two groups of individual are observed both

[^1]before and after a treatment which only affect one group. The DiD estimator captures the treatment effect, namely the difference in outcome among the treated group, compared to the untreated group. The treatment effect is identified also when the groups have different initial outcome levels, while the design requires the groups to have common trends.

## 3 Summary of papers

## Climbing the Ranks: Incumbency Effects in Party-List Systems Co-author: Jon Fiva

The first paper examines the role of incumbency in electoral politics. At the point of departure, incumbents tend to have a solid electoral advantage in candidate-centered electoral settings, where an incumbent's popularity is shown to stem from pork-barreling (e.g., Mayhew, 1974; Alvarez and Saving, 1997)), the deterrence of high-quality challengers (e.g., Cox and Katz, 1996; Hall and Snyder, 2015), and activities that increase name recognition (e.g., Mann and Wolfinger, 1980; Kam and Zechmeister, 2013). Incumbency effects may also exist in party-centered environments, but the relevant mechanisms are likely to differ. In list-based electoral systems, party elites may contribute to the electoral success of incumbents through the nomination process (Llaudet, 2014; Golden and Picci, 2015). In this paper we use data from Norwegian local elections to estimate incumbency effects. The open-list electoral setting facilitates two types of RD designs that together allow us to isolate various components of the incumbency advantage. Specifically, we exploit that seats are first allocated across parties, and then to candidates within lists. In our main analysis we compare bare winners to bare losers running for office on the same party list. This allows us to isolate the personal incumbency advantage, and explore the underlying mechanisms. The second RD design exploits discontinuities in the seat allocation formula to obtain quasi-experimental variation in parties' representation in the council. By putting results from these two RD designs together, we aim to elucidate
how the electoral advantages from holding office materialize in party-list systems.
We find evidence of a substantial personal incumbency advantage. The probability of a candidate winning a seat in the subsequent election is estimated to jump from 0.21 to 0.30 when comparing bare losers to bare winners. We find no clear evidence that voters contribute to this personal incumbency advantage. Rather, the results indicates that party elites are instrumental in securing the electoral success of their party affiliates. Incumbents and non-incumbents run again in the subsequent election at about equal rates. However, incumbents tend to advance in the party hierarchy and obtain safer ballot positions in future elections, which is what ultimately leads to electoral success. The parties, on the other hand, is not found to have an electoral advantage in the subsequent election. Parties that just miss out on their first seat receive about the same share of seats in the next election as parties that just won their first seat. Taken together with our other findings, this suggests that voters' contribution to the personal incumbency advantage is small or non-existent.

## Free to Switch or Switched Off? Consumer Heterogeneity in Choice of Mobile Subscriptions

The second paper examines the choice of switching price plan within mobile subscriptions. Consumers do not always choose the most cost-minimizing offer, even though products are highly homogeneous. Such behavior is often explained with reference to search costs, switching costs and/or preference biases. In this paper, I exploit rich customer data from a mobile operator to study how price plan switching within an operator is influenced by an opportunity to switch to a less expensive plan. An unanticipated launch of a new range of price plans, changed the available plans to switch to, i.e. customers' outside option. The launch created a difference in the amount each customer could save if they switched to the least expensive price plan, and this difference allows me to estimate the extent to which the introduction of a cheaper outside option resulted in more switching
of price plans.
When the company introduced its new price plan portfolio, they virtually doubled the rate at which existing customer switched plan. Surprisingly, the difference in the amount a customer could potentially save from switching price plan has no effect on the increase in switching rate, i.e. customers that have less to save from switching with the new price plans compared to the old plans, still increase their tendency to switch to the same extent as customers with more to save from switching under the new scheme. Even though the difference in potential savings can not explain price plan switching, the difference in what a consumer potentially can save from switching relative to their current expenditure gives the predicted results: customers facing an increase in potential savings from switching price plans, relative to costs, are significantly mores likely to switch than customers with lower potential savings from switching, relative to costs. The results are in line with two strands of the literature. First, the literature on reference dependence, (cf., Kahneman and Tversky, 1979), which shows that individuals tend to value changes not by the change itself, but relative to certain reference points. Second, the literature on rational inattention (Sims, 2003), argues that low income consumers will tend to minimize cost more than high income consumers. As income is likely to correlate with costs, the result showing that relative changes do in fact matter, can be an implication of rational inattention.

## The Poking Effect: Price Changes and Inertia in the Market for Mobile Subscriptions Co-authors: Bjørn-Atle Reme and Morten Sæthre

The third paper studies consumer inertia in the mobile subscription market. Particularly, we focus on consumers' decision to switch to competing providers. We exploit major changes to the tariffs faced by almost 300,000 consumers of a large telecom provider, to identify the effect of price changes on the propensity to switch provider. The propensity to switch increases, also for consumers who would pay less under new tariffs. We label this
response the "poking effect" - the price change causes consumers to reopen a previously closed decision. Our findings suggest existence of choice inertia, as the universe of plans offered in the market was otherwise stable around the period of the tariff change. Furthermore, we find that the propensity to switch is at its highest at time when consumers are informed about the upcoming change, one month prior to the tariff changes. The strong response prior to being affected by new terms, implies that active choice behavior can be induced even without learning from experience with new prices. There is at least one obvious mechanism of this "poking effect", which we can not rule out: When an operator change prices, consumers perceive the price change to be to their disadvantage. In markets with complex prices and uncertain consumption, consumers may not calculate the expected outcome of new prices. They may rather base their decisions on simpler rules, such as: if the operator changes the price, my expenditures will increase.

We estimate a discrete choice model inspired by Hortaçsu, Madanizadeh and Puller (2017), allowing us to separate the effect of the poke on consumer attention from the effect of removing consumers' current plans. Estimating the model shows that the information about the price change more than double the share of consumers being attentive. Our results have managerial implications for service providers, in particular those with a complex price structure. Managers should be aware that changes in terms and conditions could cause an increase in churn, not only for customers who are worse off, but also for those who are better off. This poking effect can to some extent be mitigated by clearly explaining customers that the change is to their advantage, when it actually is to their advantage. However, and as shown by Ascarza, Iyengar and Schleicher (2016), it is not necessarily sufficient.

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## Chapter 2

## Climbing the Ranks:

Incumbency Effects in Party-list Systems

Paper 1 of this dissertation (pages 14-42) is not available open access, due to copyright matters.

## Paper 1

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## Chapter 3

Free to Switch or Switched Off?
Consumer Heterogeneity
in Choice of Mobile Subscriptions

# Free to Switch or Switched Off? Consumer Heterogeneity in Choice of Mobile Subscriptions* 

Helene Lie Røhr ${ }^{\dagger}$


#### Abstract

Consumers do not always choose the most cost-minimizing offer, even though products are highly homogeneous. Such behavior is often explained with reference to search costs, switching costs and/or preference biases. In this paper, I exploit rich customer data from a mobile operator to analyze how the opportunity to reduce expenditures affects customers' readiness to switch price plans within the same operator. The data cover a major but unanticipated change in price plans. The operator's pre-launch customers, are allowed to keep their old plan, but if they did want to switch, their outside option would be changed. This allows me to estimate the impact of the opportunity to reduce expenditures from switching plan, on price plan choice. Surprisingly, changes in the possibility to save from switching price plan do not influence the decision to switch, while the launch of the new price plans did persuade customers to switch. This behavior indicates that customers are inert, and that the launch reduced inertia. Even though the opportunity to save by switching in absolute terms does not influence switching behavior, the possibility of saving relative to total cost does matter. This behavior is in line with both the theory of reference dependence and rational inattention.


Keywords: Consumer switching, Mobile subscriptions, Consumer inertia, Reference dependence.

[^2]
## 1 Introduction

In the choice between homogeneous products, standard utility maximization implies choosing the product with the lowest price. Nevertheless, there is evidence of consumers failing to opt for the lowest price, also in markets where products or services are more or less homogeneous (Grubb, 2015b). Many of the examples where consumers fail to choose the lowest price stem from the service industry, such as telecommunication, banking, insurance, cable TV and electricity. In the service industry, several factors complicate the purchase decision. Consumers typically enter a price plan ex ante consumption and the purchase is periodically billed and often automatically renewed, unless explicitly stopped. Prices tend to be non-linear, multi-dimensional, and products are sold as bundles.

In this paper, I analyze the behavior of customers of a company in the service industry displaying all of the above mentioned characteristics, namely a telecom provider. I concentrate on the demand side, and study how price plan switching within the operator is influenced by an opportunity to switch to a less expensive plan. An unanticipated launch of a new range of price plans, changed the available plans to switch to, i.e. customers' outside option. The launch created a difference in the amount each customer could save if they switched to the least expensive price plan, and this difference allows me to estimate the extent to which the introduction of a cheaper outside option resulted in more switching of price plans.

When the company introduced its new price plans, they virtually doubled the rate at which existing customer switched price plan. Surprisingly, the difference in the amount a customer could potentially save from switching price plan has no effect on the increase in switching rate, i.e. customers that have less to save from switching with the new price plans compared to the old plans increase their tendency to switch to the same extent as customers with more to save from switching under the new scheme. Switching seems to be driven by the launch itself-or by the marketing campaign accompanying the launch. I therefore interpret the increase in the rate of plan switching following the launch as
the result of reduced inertia (increased attention), rather as an attempt by customers to reduce costs (cf. Handel, 2013).

Even though the difference in potential savings can not explain price plan switching, the difference in what a consumer potentially can save from switching relative to their current expenditure gives the predicted results: customers facing an increase in potential savings from switching price plans, relative to costs, are significantly mores likely to switch than customers with lower potential savings from switching, relative to costs. The results are in line with two strands of the literature. First, the literature on reference dependence, (cf., Kahneman and Tversky, 1979), which shows that individuals tend to value changes not by the change itself, but relative to certain reference points. Second, the literature on rational inattention (Sims, 2003), argues that low income consumers will tend to minimize cost more than high income consumers. As income is likely to correlate with costs, the result showing that relative changes do in fact matter, can be an implication of rational inattention.

Grubb (2015b) provides a tripartite summary of the literature on why consumers fail to choose the lowest price: ${ }^{1}$ consumers search too little (cf. Goettler and Clay, 2011); consumers exhibit inertia which results in too little switching from past choices (cf. Handel, 2013); and consumers are confused about prices because prices are complex and/or consumers mis-weight product attributes. The combination of complex or non-linear prices and preference biases are analyzed in numerous papers. Grubb (2009) shows that customers are overconfident regarding fluctuations in future demand. Flat rate biases, when consumers prefer flat rates to pay-per-use - also when the flat rate is more expensive - are found with internet access (Lambrecht and Skiera, 2006) and gym memberships (DellaVigna and Malmendier, 2006). Similar results include Ater and Landsman (2013), who find overage aversion ${ }^{2}$ in credit card use; and Genakos, Roumanias and Valletti (2015), who find that loss aversion plays a major role in choice of mobile phone price plan. On the

[^3]other hand, Miravete (2003) found cost-minimizing behavior in the US telecom market, though learning took longer for consumers holding a flat rate tariff compared to those with a pay-per-use tariff. Miravete and Palacios-Huerta (2014) show that even though potential savings are low, mistakes in tariff choices are not permanent.

A commonly applied pricing scheme in the service industry, including the company which has provided me with data, is the three-part tariff setup. Consumers then pay no marginal price within the included allowance, but face a marginal price of consumption if they use beyond the allowance. Consumers therefore face an imbalance regarding variation in consumption and expenditures. Consumption lower than the included allowance does not reduce expenditure, while consumption above the included allowance does. Lambrecht, Seim and Skiera (2007) show that demand uncertainty under threepart tariffs lowers consumer surplus, inasmuch as consumers with high uncertainty tend to choose price plans with a higher allowance and a higher monthly fee. paper

## 2 Data and market

To study the switching of plans offered by a single mobile operator, I exploit a data set provided by a Nordic mobile operator, covering a period from October 2013 to June 2015. The proprietary monthly panel data are based on billing information containing consumption, expenditure, and price plan choice, including binding contracts, in addition to individual characteristics such as customers' age, gender, and zip code. The data set covers the universe of the mobile operator's post-paid customers, while about 600,000 are included in the analysis. ${ }^{3}$ The analysis is limited to domestic consumption. ${ }^{4}$ I conduct the analyzes on customers whom all hold three-part tariffs, i.e. price plans including allowances for voice minutes, SMS and/or megabytes of data. Most customers have

[^4]allowances on all three, where voice and SMS are unlimited. Customers receive an SMS when they exceed their data allowance to avoid unexpected high bills. ${ }^{5}$ When the data allowance is exceeded, consumers can choose to buy additional data packages or pay a marginal price per megabyte. ${ }^{6}$ Finally, there are no monetary costs related to switching price plans offered by the operator. ${ }^{7}$

The Nordic mobile markets are mature, and consumers have considerable experience of mobile price plans as mobile penetration has exceeded 100 percent (more mobile price plans than people) over the past ten years. The markets are dominated by postpaid price plans, and there are three dominating operators covering more than 90 percent of the market. The data set is derived from an operator with $25-55$ percent of the market, and the average monthly revenue per customer (ARPU) is in the range of $15-30$ Euros. At time of data collection, most customers were buying three-part tariffs, with unlimited voice minutes and SMS being very common. Hence, data bundles, i.e. a combination of the monthly fixed fee and a given volume of data, dominate the market.

## 3 Launch of a new portfolio of price plans

In the beginning of May 2014, the operator launched a new portfolio of price plans. Customers were informed about the launch through a mass marketing campaign. ${ }^{8}$ Price changes of this magnitude happen about every second year, being, naturally, a response changes in the market. ${ }^{9}$ From time to time, the operator does major structural changes

[^5]to the price plans, while in this case the price change were only an adjustment of the price points and included volumes. On average, the new plans reduces the price per MB.

Customers were not forced to switch price plan after the launch - they could keep their old price plan, but it is no longer offered to others. Customers can switch, at any point in time, to another price plan offered by the operator in the market. When the operator introduced a new range of price plans, customers are not allowed to switch to plans sold before May, and those wishing to switch can only choose from the newly launched plans. Hence, for a customer wishing to switch price plan, the outside option is different. So is the hypothetical amount a customer could have saved by switching price plans, potential savings.

The left-hand panel of Figure 1 shows an almost doubling of price plan switching rates at the time when the of new prices are introduced (vertical dashed line in Figure 1). In April, prior to the launch, about 2.5 percent of consumers switched price plan every month. The new price portfolio was launched in the beginning of the next month, and in that month about 4.5 percent of the operator's customers chose to switch price plan. ${ }^{10}$ The middle panel of Figure 1 shows that churning, i.e. customers leaving the company, is relatively stable throughout the period, while there is no obvious increase in consumer acquisition that is attributable to the launch of new plans, indicating that the launch has mainly had an effect on existing consumers (right panel). The following analysis will concentrate on understanding how the launch of the new price plans influenced switching within the company, meaning the increase in switching rates in the left-hand panel of Figure 1.

[^6]Figure 1: Monthly price plan switching rates and churn rates, in percent


Note: The figure to the left shows percentage of consumers switching price plans within the operator each month, while the middle figure shows percentage of consumers leaving the company (churn) each month. The right-hand figure shows monthly customer acquisition rate. The vertical line in each figure marks the launch of new price plans. Churn rates and customer acquisition rates are not comparable, as the acquisition numbers include all new customers and the customer base comprise customers subscribing to the price plans recently sold on the market. The operator loses, in total, about the same number of customers as it acquires.

### 3.1 Potential saving

A consumer can potentially save money or reduce expenditures by switching to another price plan (within the operator). Potential saving are defined as an ex post assessmentwhat consumption amounted to last month, and what the cost of the different plans would be. Hence, potential savings are the difference between the actual cost of the chosen price plan and that of the optimal price plan, given actual consumption that month. ${ }^{11}$ Letting $k^{*}$ denote the cost-minimizing price plan, and $X_{i, t}$ the consumption of individual $i$ in period $t$, I define potential savings for individual $i$ in period $t$ by the difference between the cost of the cost-minimizing plan and the chosen plan, as in Equation 1.

$$
\begin{equation*}
\text { PotentialSavings }_{i, t}=\operatorname{Cost}\left(k_{i, t}^{*} \mid X_{i, t}\right)-\operatorname{Cost}\left(k_{i, t}^{\text {ChosenPriceplan }} \mid X_{i, t}\right) \tag{1}
\end{equation*}
$$

The definition of potential saving is an analog of the "above minimum spending" used by Ketcham, Lucarelli and Powers (2015). They interpret above minimum spending as the cost of staying on the status quo plan among health insurance plans (Medicare Part D). Similarly, Miravete (2003) and Miravete and Palacios-Huerta (2014) use "potential

[^7](predicted) savings" as what a consumer would have saved if he had switched to the alternative option ${ }^{12}$ keeping consumption constant.

The left-hand panel of Figure 2, shows the histogram of potential saving in one month. That month, about 25 percent of the customers held the cost-minimizing offer, while almost 20 percent could have reduced their expenditure by 30 Euros or more. A histogram of each customers's average potential saving in the period before the new portfolio was launched is shown in the right-hand panel. About 5 percent of customers had always a zero potential saving, and 25 percent of customers could save on average 5 Euros or less per month. The average customer pays almost 12 Euro above the minimum spending figure. ${ }^{13}$

Figure 2: Histogram of potential savings before launch of new plans


Note: The left-hand panel shows the histogram of each customers' monthly potential savings in the month before the new price scheme. The shape of the histogram with spikes is due to the structure of the price plans, giving most customers a potential savings in the five multiplier. The right-hand panel shows the histogram of each customer's average potential savings during the pre-period. The histograms are truncated at 40 . The dashed line indicates the average potential savings, which is 11.7 .

Calculating potential savings is an ex post assessment: given the previous month's consumption, which price plan would have been the cheapest? The choice of price plan, on the other hand, is taken ex ante consumption. If the previous month's potential saving were decisive for current month's price plan choice, consumption would need to

[^8]be relatively stable from month to month. Figure 3 shows the scatter plot of potential saving (upper left-hand panel) in April, the month prior to the new prices ( t ) compared to March, two months before $(t-1) .{ }^{14}$ The high correlation in potential saving is due to the correlation in minutes (upper right-hand panel), SMS (lower left-hand panel), and megabytes (lower right-hand panel). The corresponding correlation coefficients are high; 0.87 for minutes; 0.88 for SMS; and 0.78 for megabytes. The average consumption throughout the sample period is stable, but with a steady increase in data, cf. Figure A. 2 .

Figure 3: Correlation between consumption in $t$ and $t-1$


Note: The figures are scatter plots of potential saving (upper left hand panel) or consumption in $t$, the month before the portfolio launch, (April) and t-1, two months before the portfolio launch (March). All figures are capped at respectively 60 Euros, 3000 minutes, 2000 SMS and 10,000 megabytes.

To decide which price plan to switch to, the customer needs to predict future consumption. It is a fair assumption that customers base that prediction upon current consumption. Still, changes in marginal prices may change consumption levels. Look-

[^9]ing at the usage patterns of customers that switched price plan the first three months after the launch, Figure 4, we see that the use of voice minutes and SMS is completely unchanged. Marginal prices of voice and SMS are almost irrelevant: about 90 percent of customers subscribe to price plans with unlimited voice and SMS use. Megabytes of data, on the other hand, are never truly unlimited in any price plan, and as the lower left-hand panel of Figure 4 shows, customers increase consumption of megabytes of data after switching price plan. However, on average, customers switch to plans with more included usage (cf. the lower right hand panel of Figure 4), and use on average far less than the amount of data in their price plans. ${ }^{15}$

If customers expect an increase in consumption, the size of potential savings is overstated for customers that have chosen a price plan with "too much" included usage, while it is understated for customers that have chosen price plan with "too little" included volumes. 23 percent of the customers could have reduced their expenditures, had they switched to a price plan with higher allowances.

### 3.2 Unanticipated change in potential savings

The launch of a new range of price plans changed the amount a customer potentially could save from switching price plan, and this difference is used to identify the effect of potential saving on price plan switching. To calculate the difference in potential saving, I use actual minutes spent calling, number of SMSs, and data volumes during the month(s) before the launch. Given this information, I identify the cost-minimizing price plan within the old price portfolio and the new price portfolio, and calculate the cost of the cost-minimizing plans. The change in potential savings equals the difference in cost between the old cost-minimizing price plan and the new cost-minimizing price plan. In

[^10]Figure 4: Average consumption around time of price plan switching


Note: The figure shows the average monthly consumption of consumers switching price plans in the first three months from the portfolio launch. Month 0 , indicated by the dashed vertical line, is the month the consumer switch price plan, i.e. May, June or July, dependent on when the consumer chooses to switch. Month - 5 is five months before, while 5 is five months after switching the price plan. The upper left hand panel is average voice minutes and upper hand right panel average number of SMS. Lower left hand panel shows average consumption of megabytes of data, while the lower right panel shows average level of included megabytes.
other words, the difference in potential savings is given by the difference in expenditure between the cheapest pre-launch price plan and the cheapest post-launch price plan, keeping consumption constant, as shown in Equation 2.

$$
\begin{equation*}
\text { ChangePotentialSave }_{i}=\operatorname{Cost}\left(k_{\text {OldPlans }}^{*} \mid X_{i, t-1}\right)-\operatorname{Cost}\left(k_{\text {NewPlans }}^{*} \mid X_{i, t-1}\right) \tag{2}
\end{equation*}
$$

ChangePotentialSavings ${ }_{i}$ denotes the difference, due to the launch, in potential saving, experienced by individual $i . k^{*}$ is individual $i$ 's cost-minimizing price plan given consumption, $X_{i, t-1}$, which is the minutes called, number of SMSs, and data volumes used by individual $i$ the period before the launch.

Figure 5 shows the histogram of the change in potential saving from Equation 2. For about 35 percent of customers, the cheapest price plan they could have switched to is now more expensive and the change in potential savings is negative (dark grey area). About 55 percent of customers face no change in what they potentially could save from switching (light grey bar), while about 10 percent of customers could save more from switching (black area).

Figure 5: Distribution of change in potential savings


Note: The figure shows the histogram of the change in potential savings introduction of the new price plans according to Equation 2. The grey area shows customers that, due to the new portfolio, would save less from switching ( $N=188,246$ ). The light grey bar at zero is the share of customers with no changes in the amount they could save from switching ( $N=334,921$ ), while the black area consists of customers that save more from switching ( $N=57,782$ ). The histogram is truncated at +10 . Customers facing an increase in potential savings is up to +19.5 .

The following results are dependent on the validity of the change in potential savings. Hence, as a robustness test of this calculation, I use different measures of consumption before the launch, ( $X_{i, t-1}$ ). The baseline results are conducted on consumption the month before the new prices were introduced, i.e. April 2014. Two alternative measures for preconsumption are calculated. The first, uses average consumption February to April, the second, the highest consumption of voice, SMS, and megabytes throughout the entire pre-period. ${ }^{16}$

### 3.3 Identification

The question of interest is whether the change in plan switching is different for customers that potentially can save more from switching after the price launch, compared to consumers that potentially can save less. To investigate whether the change in switching rates differ for these groups, I estimate the following difference-in-difference equation:

$$
\begin{equation*}
\text { Switch }_{i, g, t}=\gamma_{g}+\lambda_{t}+\beta\left(\gamma_{g} * \lambda_{t}\right)+Z_{i} \nu+\epsilon_{i, t} \tag{3}
\end{equation*}
$$

Switch $_{i, g, t}$ takes the value 1 if customer $i$, in group $g$, switches price plans in period $t$, and zero otherwise. $\gamma_{g}$ is a vector of dummies for each group of customers, grouped by size of change in potential savings. $\lambda_{t}$ is a vector of period dummies. The data are monthly, but to simplify the reporting of estimation results, I group the months by three. This gives me two periods prior to the portfolio launch, and five after. $Z_{i, t}$ is a vector of individual specific control variables: age, gender, municipality of residency, including municipality level covariates. $\epsilon_{i, t}$ are cluster-specific errors. ${ }^{17}$ For the estimates of $\beta$ to be valid, the assumption of common trends between each group needs to hold.

Table 1 shows summary statistics for the three groups: customers with decreased potential savings, customers with no change in potential savings (neutral), and customers

[^11]with increased potential savings. On the demographics, the groups are relatively well balanced-all three groups have an almost equal gender balance, and do not differ much with respect to age. The balance of municipality characteristic, population, unemployment and income shows that, on average, the three customer groups live in similar types of municipality. The share of the three groups living in the four largest cities shows the same. Importantly, these customer groups could all have saved from switching, close to the average of about 12 Euros, before the launch of new plans. In addition, they are fairly similar regarding length of time on current price plan (months tenure), while monthly switching rate among the customer with decreased potential savings is slightly lower than for the two other groups. By definition, these customers cannot be equal-they have to differ in either pre-consumption or price plan choice or both. If not, they would not see any differences in potential savings. The customers with decreased potential save are, on average, lower volume users in terms of voice minutes, SMS, and megabytes of data.

## 4 Results

When the new price plans were launched, about 45 percent of customers saw a change in what they potentially could save from switching price plans. Assuming that saving money is the only reason to switch price plan, the naive prediction of changes in switching rates from the launch of new plans is the following: i) customers who can save more from switching after the launch switch more (increased potential savings); ii) customers with the same potential savings before and after the launch (neutral group) switch at the same rate; while iii) customers who will save less from switching after new prices are introduced switch less. Figure 6 shows switching rates for each of these three groups. The introduction of the new plans is indicated by the dashed vertical line. Customers with a lower potential to save have lower switching rates compare to the two other groups, but surprisingly, there is no obvious difference between the groups in the rate of change in switching after the new portfolio was launched. Switching increases by about two

Table 1: Summary statistics

|  | $(1)$ |  |  | $(2)$ |  | $(3)$ |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Decr. pot. savings | Neut. pot. savings | Incr. pot. savings |  |  |  |  |
|  | Mean | SD | Mean | SD | Mean | SD |  |
| Female | 0.48 | $(0.50)$ | 0.53 | $(0.50)$ | 0.53 | $(0.50)$ |  |
| Age | 52.89 | $(13.79)$ | 44.45 | $(13.41)$ | 42.62 | $(12.04)$ |  |
|  |  |  |  |  |  |  |  |
| Population | 96,791 | $(178,231)$ | 103,618 | $(186,289)$ | 105,123 | $(187,482)$ |  |
| Unemployment | 0.02 | $(0.01)$ | 0.02 | $(0.01)$ | 0.02 | $(0.01)$ |  |
| Income | 485,484 | $(51,817)$ | 483,980 | $(51,045)$ | 485,289 | $(51,341)$ |  |
|  |  |  |  |  |  |  |  |
| Share with residency in: |  |  |  |  |  |  |  |
| The largest city | 0.09 | $(0.28)$ | 0.10 | $(0.30)$ | 0.10 | $(0.30)$ |  |
| 2nd largest city | 0.04 | $(0.20)$ | 0.04 | $(0.20)$ | 0.04 | $(0.20)$ |  |
| 3rd largest city | 0.03 | $(0.16)$ | 0.03 | $(0.17)$ | 0.03 | $(0.17)$ |  |
| 4th largest city | 0.02 | $(0.14)$ | 0.02 | $(0.13)$ | 0.02 | $(0.13)$ |  |
|  |  |  |  |  |  |  |  |
| Potential savings | 11.55 | $(6.70)$ | 11.66 | $(10.48)$ | 13.49 | $(10.29)$ |  |
| Subscr. tenure, months | 11.53 | $(8.57)$ | 10.17 | $(8.01)$ | 10.08 | $(7.90)$ |  |
| Switching rate | 3.40 | $(9.74)$ | 4.40 | $(9.16)$ | 4.26 | $(9.00)$ |  |
| Change, pot. savings | -6.19 | $(3.22)$ | 0.00 | $(0.00)$ | 4.97 | $(3.21)$ |  |
| Megabytes | 140.06 | $(550.77)$ | 716.75 | $(979.02)$ | 734.64 | $(1063.58)$ |  |
| Minutes | 116.03 | $(98.95)$ | 332.72 | $(333.49)$ | 280.04 | $(300.98)$ |  |
| SMS | 64.47 | $(77.57)$ | 165.78 | $(213.31)$ | 168.23 | $(194.35)$ |  |
| N | 188,246 |  | 334,921 |  | 57,782 |  |  |

Note: Sample is restricted to customer in the customer base throughout the pre-period, meaning that both customers leaving the operator and newly acquired customers before the portfolio launch, are excluded. Population, unemployment and income are all municipality averages. Consumption of minutes, SMS, and megabytes is average before the new plans.
percentage points (70-80 percent) for all groups.

Figure 6: Monthly share of customers switching price plans by changes in potential saving


Note: The figure shows percentage of customers switching price plans each month split on their change in potential savings: decreased, no change (neutral), and increased potential save. The vertical line in each figure indicates the time of the portfolio launch.

The mobile operator's introduction of new price plans was accompanied by a marketing campaign to heighten the firm's public profile and raise brand awareness aiming, while giving information about the new prices. Hence, we cannot assume that the launch went unheeded, even for a customers with a decreased potential of gain from switching. If customers are inert or inattentive, it would therefore be reasonable to expect an increase in switching among all customers after the new portfolio came on line. What is surprising, is the little difference in switching rates between customers with higher and lower potential savings. ${ }^{18}$

As Figure 6 shows, customers with less to save from switching, increase their switching

[^12]rate as much as customers who save more from switching. However, the analysis does not take into account whether the change in potential savings from switching is small or large. Customers are more likely to respond to a larger change than a small one. To test if the size of the difference in potential savings matters for customers' tendency to switch plan, I estimate separate results for customers experiencing a change (increase or decrease) in potential savings which constitutes for more than five Euros. ${ }^{19}$ Figure 7 reports on the estimated $\beta \mathrm{s}$ from Equation 3, and shows the difference in switching rates for customers who could save by switching compared with consumers who would not. Period two is used as the reference period. If consumers with increased potential savings switched more after the new tariffs, we would observe a positive point estimate for this group in period three (the portfolio launch of the new portfolio is marked by a dashed line). The point estimates are not statistically significant from zero in any period, meaning that none of these customer groups switch significantly more or less compared to the neutral group. Standard errors are clustered by initial choice of plan under similar market conditions. That means that standard errors are clustered by a combination of the price plan customers held in April 2014, and how many months each consumer have subscribed to that particular plan. The monthly switching rates of customers with an increased potential savings are very similar to those of the neutral group, and the point estimates in the lower left hand panel are therefore precise. The point estimates in the upper left-hand panel are based on fewer observations $(\mathrm{N}=3,346)$ than the other groups. The customers with a lower potential savings are more heterogeneous in their switching rates, and the point estimates are less precise. ${ }^{20}$

[^13]Figure 7: Regression results with 95 percent CI
Panel A: Change in potential savings above 5 euro



Panel B: Change in potential savings, 5 euro and less



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta s$ are estimated per time period. The vertical line indicates the launch of new price plans. The upper left-hand panel shows results for customers for whom an increase in potential savings exceeds five Euros $(N=3,346)$, while the upper right-hand panel shows results for customers whose potential to save is decreased with five Euros or more $(N=124,418)$ The lower left-hand panel compares consumers with an increase in potential save of five Euros or less $(N=54,436)$ to the neutral consumers, and the lower right-hand panel do the same for the customers who have a decreased potential savings of five Euros or less $(N=63,828)$. Robust standard errors clustered at subscribers entering the same ex ante price plan under similar market conditions (i.e. ex ante price plan and tenure), 315 clusters.

## 5 Mechanism

When the new plans were made available to the public, the proportion of customers switching plans almost doubled, irrespective of changes in potential savings (cf. Figure 6). Since the change in potential savings does not explain price plan switching, what are the plausible mechanisms that can do so? The new price plans were marketed, and the marketing campaign was intended both to increase awareness and inform about prices. The increase in switching by consumers with a lowered potential to save is a clear indication that the marketing campaign affected customers. Customers who the month before the new prices were introduced would have saved more by switching, switched to a higher extent after the launch. Assuming that customers are inattentive, the launch of new plans and accompanying marketing campaign increases attention and hence switching rates. ${ }^{21}$

Consumers are heterogeneous, and responses to price changes will therefore vary. In the sections to follow, I concentrate on three dimensions of heterogeneity: income (rational inattention); mobile expenditures (reference dependence); and ex ante potential savings (cost-minimizing preferences).

### 5.1 Rational inattention

Customers' motivation to minimize costs is likely to vary with income, and in the Nordic markets the cost of a mobile subscription constitutes a very small part of customers' total expenditure. In fact, spending on all telecom services in the relevant market only amount to about 1-2 percent of total expenditures. Taking the time to reduce these cost may be considered an unnecessary effort, and customers may consequently not react to opportunities to reduce costs. If what I observe is a result of rational inattention

[^14](cf. Sims, 2003), customers in the lower income bracket would be more likely to react to changes in their possibility to save money, compared to customers in higher income brackets. I have information about customers' place of residency, and I therefore use municipality median income as a proxy for customers' income, ${ }^{22}$ and split customers into income deciles. Figure 8 compares switching in the lowest income decile to that in the highest income decile. The response to the change in potential savings by low income and high income customers is very similar. ${ }^{23}$ Hence, based on median income in consumers' area of residency, there is no support for the hypotheses of rational inattention.

Figure 8: Price plan switching rates: by highest and lowest income decile


Note: The figure shows switching rates in percent of customers with registered postal code with the lowest decile median income and the highest decile median income respectively (municipality median income and administrative area median income in the biggest city). The left hand panel shows switching rates among the consumers in the lowest income decile, while the right hand panel shows switching rates by consumers living in areas with the highest income decile.

The weakness of the preceding analysis is that the measure of income is based on residence municipality (administrative area), and relevant individual variation may have been averaged out. ${ }^{24}$

[^15]
### 5.2 Relative changes

Choices are dependent in a variety of situations on reference points, cf. Kahneman, Knetsch and Thaler (1991), and potential gains and losses should in these situations be evaluated relative to that reference point. Customers' expenditure level when the new prices are introduced is a natural reference point for evaluating price plan switching: given current costs, what are the gains relative to those costs? I therefore, analyze the change in potential savings relative to individual cost levels before the new plans were introduced. The left-hand panel in Figure 9 shows the histogram of change in potential savings relative to costs. Since a small number of customer could save more than 20 percent of their cost, I restrict the sample to customers whose potential to save money constitute at least 20 percent of their current costs. The right-hand panel in Figure 9 compares the switching rates of the neutral group to the switching rate of these customers facing a change in potential savings of at least 20 percent of their costs. Contrary to the results in Figure 7, customers with the possibility of saving at east 20 percent of their costs, are much more likely to switch after the new prices are introduced compared to the other customers. Point estimates with 95 percent confidence intervals are plotted in the Appendix, Figure A.8.

Customers respond to changes in the amount they potentially can save from switching, when that amount is large enough compared to their costs. That result is in line with the literature on reference dependence. It is the value relative to a reference point that matter, and in this case current costs are a natural reference point. However, expenditures on mobile subscriptions are likely to be correlated with income. High income customers spend more on their mobile subscription compare to low income customers. The fact that relative changes matters may be a consequence of rational inattention-high income customers with high costs do not care that much about the opportunity to reduce costs as low income customers with low costs. However, operator's survey evidence ${ }^{25}$ reveal no correlation between customers' actual mobile expenditures and stated household income.

[^16]Figure 9: Change in potential saving relative to ex ante costs


Note: The left-hand panel shows the histogram of the change in potential saving relative to the customers' pre costs (in percent). The grey area shows customers that, due to the new portfolio, face a decrease in what they can save from switching of at least 20 percent of current costs. The light grey area represent customers with a change in potential savings constituting of less than 20 percent of their costs, while the black area consists of customers that, due to the new portfolio, save face an increase of at least 20 percent of current costs in what they can save from switching. The right-hand panel restricts the sample to customers with a relative change in potential saving of more than 20 percent of costs. The dark grey line shows monthly switching rates for customers with an increase in potential saving of at least 20 percent of costs ( $N=8,194$ ), while the black line includes all customers with a decrease of at least 20 percent of costs $(N=137,695)$. The light grey line represents switching rates of the customers without any change in potential savings.

### 5.3 Heterogeneous initial potential savings

Customers are heterogeneous, and their response to changes in the outside option depend on their preferences. Initial choices, including potential savings, are likely to reflect individual preferences for cost-minimizing behavior. Assuming that customers' preferences are unaffected by the introduction of new plans, customers whose initially have little to save from switching plans, would be expected to change their propensity to switch according to the change in potential savings. To determine whether customers with little to gain from switching to begin with, change their switching behavior as predicted, I split the consumers into quartiles based on their ex ante average potential savings amount. ${ }^{26}$

Figure 10 shows switching rates in the consumers for the different quartiles of average potential savings before the new price plans were launched. The upper left hand panel

[^17]shows switching rates of customers that on average could only save 5 Euros or less per month by switching in the pre-launch period. In this group, the customers with less potentially to save do not increase their switching rate substantially after the introduction of new prices are launched, and compared to the neutral group, the point estimate of $\beta$ is negative. ${ }^{27}$ The difference is significant, both statistically and in magnitude, meaning that consumers with lowered potential savings, in the lowest quartile of pre-launch average potential savings switch less compared to the neutral group. The customers whose potential savings has grown, still switch at about the same rate as the neutral consumers.

Figure 10: Price plan switching rates: consumers with low ex ante potential saving


Note: The figure shows monthly switching rates in percent for customers in the quartile with lowest pre-launch potential saving compared to customers in the quartile with highest pre-launch potential save. The left hand panel shows switching rates among the customers with increased potential savings. The right hand panel shows switching rates among consumers with decreased potential savings.

## 6 Discussion and conclusion

There is evidence showing that consumers tend to not cost-minimize, when buying products from the service industry, even though the products often are nearly homogeneous. I

[^18]find similar patterns, a large proportion of the consumers of a mobile operator could have reduced their expenditures if they had chosen another price plan from the same operator.

By exploiting an exogenous change to the outside option (the launch of new price plans), I study how customers switch price plans, depending on whether the new outside option is more or less expensive than the old. Customers do not react to changes in the outside option as anticipated; customers for whom a switch would involve a reduction in how much they can save from switching, will tend to switch as much as customers for whom switching would represent a gain in savings. The result is independent of the size of the difference in how much a customer could save from switching. Even when the difference in what customers can save from switching is large, they do not change their propensity to switch any more than customers with a small difference in potential savings. The potential to reduce expenditures is not decisive for the decision to switch plan. Rather, switching of price plans seems to be driven by other events such as the launch itself. If the opportunity to save money does not explain the switching decision, it is not surprising that consumers do not subscribe to the cost-minimizing price plan.

I find evidence of consumer inertia. The launch of new range of price plans accompanied by a marketing campaign could have influenced customer in two ways. First, they may learn more about market prices. ${ }^{28}$ Second, they could become more attentive to their mobile subscription, and to the existence of other plans. Insofar as the tendency to switch price plans increases independently of the change in how much the customer can save by switching, it is clear evidence of reduced consumer inertia.

Businesses operating in similar markets will often observe that their customers could have saved by switching to another price plan. Such customer behavior clearly yields positive revenues to the company in short term. Nevertheless, as a company, persuading customers to refrain from leaving is of great value, and much effort is put into loyalty programs. Offering the customer a better deal would seem like the obvious move, although it turns out that doing so can backfire. Ascarza, Iyengar and Schleicher (2016) use data

[^19]from a mobile operator to study customers' decision to leave a company. They find that customers churn more readily when they are offered to switch to a cheaper price plan of their current provider. Hence, by offering the customer the cheaper product, the company not only reduces its short term income, it also increases the probability that the customer leaves. A supporting explanation of this behavior is that the information about the cheaper price plan stimulates the consumer's attentiveness.

The rich customer data allow me to analyze heterogeneity in the response to a new outside option. Customers' initial choices reflect their preferences, and customers with low initial potential savings will likely have preferences towards cost-minimizing alternatives. I find that customers who before the launch had chosen the cost-minimizing offer, do not increase their propensity to switch when the outside option is worsen from the introduction of new plans. As all other customers increase their propensity to switch from the portfolio launch, I interpret this result as showing that customers with a low initial potential to save respond more as standard economic theory predicts.

Customers are heterogeneous in their consumption and expenditure levels. Analyzing the change in potential savings relative to costs reveal that customers faced with a large relative improvement by switching to the outside option more than triple their switching rates. This result can be interpreted in at least two ways: i) customers use costs as a reference point, and exhibit reference dependent behavior; ii) costs are correlated with income, and customers exhibit rational inattention. Using income in customers' place of residence, do not support that the behavior is a consequence of rational inattention. Additionally, survey evidence from the operator reveals low correlation between selfreported income and actual mobile expenditures. However, based on the data available, I cannot rule out rational inattention as a mechanism.

The data are from a mature market with high incomes and low mobile expenditures, ${ }^{29}$ and customers may perceive their current costs as acceptable. Additionally, what a

[^20]customer stands to gain from switching, is an opportunity cost. Kahneman, Knetsch and Thaler (1991) observe 'people treat opportunity costs differently than out-of-pocket costs. Foregone gains are less painful than perceived losses'. What I find may be an instance of exactly that. When customers have to select a plan from a list of complex tariffs, while still uncertain about future demand, the foregone gain may not hurt that much.

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## Online Appendix A: Supplementary analysis

Figure A.1: Quarterly mobile subscription and traffic revenues


Note: The figure shows the operator's normalized revenues from subscription and traffic, excluding interconnect. Revenues are normalized to 100 in Q3 2013. The dashed vertical line mark the launch of new price plans.

Figure A.2: Average consumption


Note: The figure shows the average monthly consumption of voice minutes (upper left-hand panel), SMS (upper right-hand panel), megabytes of data (lower left-hand panel), and included megabytes (lower right-hand panel). The dashed vertical line indicates the time of the price change.

Figure A.3: Regression results with 95 percent confidence interval
Panel A: Consumption the month before launch


Panel B: Average consumption three months before launch



Panel C: Highest consumption entire pre-period



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta$ s are estimated per time period (three month average). Period 2 is the base period, and the neutral customers are the base group. The vertical line indicates the launch of new price plans. The panels to the left show the regression results for consumers with increased potential savings, while the right-hand panels show the corresponding figure for consumers with decreased potential savings. Robust standard errors clustered at subscribers entering the same ex ante price plan under similar market conditions (i.e. ex ante price plan and tenure), 315 clusters.

Figure A.4: Excluding consumers on binding contracts: regression results with 95 percent CI

Panel A: Change in potential savings above 5 euro



Panel A: Change in potential savings, 5 euro and less



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals, excluding consumers on binding contracts during the pre-period. The $\beta$ s are estimated per time period (three month average). Period 2 is the base period, and the neutral customers are the base group. The vertical line indicates the launch of new price plans. The panels to the left show the regression results for consumers with increased potential savings, while the right-hand panels show the corresponding figure for consumers with decreased potential savings. Robust standard errors clustered at subscribers entering the same ex ante price plan under similar market conditions (i.e. ex ante price plan and tenure), 315 clusters.

Figure A.5: Quarterly expenditures on sales, marketing and commission


Note: The figure shows the operator's normalized expenditures on sales, marketing, and commission costs, normalized to 100 in Q3 2013. The dashed vertical line mark the launch of new price plans.

Figure A.6: By income: Regression results with 95 percent CI

## Panel A: Lowest income decile



Panel B: Highest income decile



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta s$ are estimated per time period (three month average). Period 2 is the base period, and the neutral customers are the base group. The vertical line indicates the launch of new price plans. The figure reports on results for consumers living in the lowest income decile (panel A) and consumers living in the highest income decile (panel B). The panels to the left show the regression results for consumers with increased potential savings, while the right-hand panels show the corresponding figure for consumers with decreased potential savings. Robust standard errors clustered at subscribers entering the same ex ante price plan under similar market conditions (i.e. ex ante price plan and tenure), 315 clusters.

Figure A.7: By ex ante potential savings: Regression results with 95 percent CI

## Panel A: First quartile of initial potential savings ( $0-5$ euro)




Panel B: Second quartile of initial potential savings (5-10 euro)



Panel C: Third quartile of initial potential savings (10-15 euro)



Panel D: Fourth quartile of ex ante potential savings (above 15 euro)


Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta$ s are estimated per time period (three month average). Period 2 is the base period, and the neutral customers are the base group. The vertical line indicates the launch of new price plans. The figure reports results by quartiles of customers' potential to save before the introduction of new plans. The panels to the left show the regression results for consumers with increased potential savings, while the right-hand panels show the corresponding figure for consumers with decreased potential savings. Robust standard errors clustered at subscribers entering the same ex ante price plan under similar market conditions (i.e. ex ante price plan and tenure), 315 clusters.

Figure A.8: By size of relative change: Regression results with 95 percent CI
Panel A: Relative change in potential save of at least 20 percent



Panel B: Relative change in potential save of less than 20 percent



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta s$ are estimated per time period (three month average). Period 2 is the base period, and the neutral customers are the base group. The vertical line indicates the launch of new price plans. The panels to the left show the regression results for consumers with increased potential savings, while the right-hand panels show the corresponding figure for consumers with decreased potential savings. Robust standard errors clustered at subscribers entering the same ex ante price plan under similar market conditions (i.e. ex ante price plan and tenure), 315 clusters.

Table A.1: Regression results

|  | (1) | (2) | (3) | (4) |
| :---: | :---: | :---: | :---: | :---: |
| Decr. pot. save | -0.924 | -0.913 | -0.810 | -0.793 |
|  | (0.628) | (0.627) | (0.621) | (0.616) |
| Incr. pot. save | -0.176* | -0.168 | -0.172* | -0.139 |
|  | (0.104) | (0.104) | (0.104) | (0.092) |
| Period 1 | 1.592 | 1.593 | 1.595 | 1.684 |
|  | (1.645) | (1.648) | (1.648) | (2.009) |
| Period 3 | 2.545** | 2.551** | 2.551** | 2.142 |
|  | (1.169) | (1.171) | (1.171) | (1.447) |
| Period 4 | 2.583** | 2.587** | 2.588** | 2.312 |
|  | (1.149) | (1.152) | (1.151) | (1.423) |
| Period 5 | 2.466** | 2.472** | 2.474** | 2.242 |
|  | (1.126) | (1.129) | (1.128) | (1.394) |
| Period 6 | 2.067** | 2.066** | 2.068** | 1.848* |
|  | (0.854) | (0.856) | (0.855) | (1.051) |
| Period 7 | 1.526 | 1.524 | 1.525 | 0.951 |
|  | (0.979) | (0.980) | (0.980) | (1.188) |
| Decr. pot. save period 1 | -0.550 | -0.547 | -0.545 | -0.544 |
|  | (0.980) | (0.981) | (0.981) | (0.986) |
| Decr. pot. save period 3 | -0.663 | -0.663 | -0.664 | -0.655 |
|  | (0.692) | (0.693) | (0.693) | (0.692) |
| Decr. pot. save period 4 | -0.465 | -0.459 | -0.458 | -0.450 |
|  | (0.687) | (0.688) | (0.688) | (0.688) |
| Decr. pot. save period 5 | -0.895 | -0.899 | -0.896 | -0.889 |
|  | (0.692) | (0.693) | (0.693) | (0.696) |
| Decr. pot. save period 6 | -0.851 | -0.851 | -0.848 | -0.840 |
|  | (0.533) | (0.533) | (0.534) | (0.536) |
| Decr. pot. save period 7 | -0.650 | -0.648 | -0.644 | -0.633 |
|  | (0.604) | (0.605) | (0.605) | (0.600) |
| Incr. pot. save period 1 | -0.115 | -0.119 | -0.120 | -0.112 |
|  | (0.179) | (0.182) | (0.182) | (0.157) |
| Incr. pot. save period 3 | 0.047 | 0.039 | 0.040 | 0.008 |
|  | (0.132) | (0.132) | (0.132) | (0.121) |
| Incr. pot. save period 4 | 0.087 | 0.083 | 0.083 | 0.060 |
|  | (0.127) | (0.127) | (0.128) | (0.118) |
| Incr. pot. save period 5 | 0.116 | 0.111 | 0.110 | 0.092 |
|  | (0.134) | (0.135) | (0.135) | (0.127) |
| Incr. pot. save period 6 | -0.067 | -0.062 | -0.062 | -0.079 |
|  | (0.127) | (0.127) | (0.127) | (0.119) |
| Incr. pot. save period 7 | 0.163 | 0.160 | 0.162 | 0.116 |
|  | (0.152) | (0.154) | (0.154) | (0.142) |
| Zip code fixed effect | No | Yes | Yes | Yes |
| Age and gender | No | No | Yes | Yes |
| Initial pot. save | No | No | No | Yes |

Note: The table shows regression results of Equation 3. The table shows point estimates for the difference in switching rates for respectively the group with a decreased potential to save, and with an increased potential to save, compared to customers with no change in their potential to save (this group is left out). Period 2 (left out) are the three months before the portfolio launch. Hence, the point estimates show the difference in switching rates compared to this period. Model (1) is the basic diff-in-diff without any control variables. Model (2) includes zip code fixed effects, and model (3) adds controls for age, gender and municipality characteristics. In model (4), I also include control for ex ante levels of potential savings. Robust standard errors clustered at choice of ex ante subscription (subscription and time of decision), 315 clusters. *p $<0.10,{ }^{* *} p<0.05$, , $^{* *} p<0.01$.

## Online Appendix B: Regression results with alternative clustering of standard errors

In the main analysis, I cluster standard errors by customers whose initial choice of price plan is the same. This means that customers who chose the same price plan under the same market conditions are clustered. Specifically, I cluster customers by a combination of their initial price plan and the month they chose that price plan. This implies that customers who have chosen a price plan during specific campaigns or discounts are clustered. In this Appendix, I first cluster standard errors by choice of initial price plans only. Thereafter, I treat each customer as independent and cluster observations by customers.

Clustering standard errors on initial price plans, gives me 13 cluster, which is far below warranting a belief in an asymptotical approximation. In addition, the cluster sizes are unbalanced. To still be able to cluster standard errors at initial price plans, I utilize the package clustse in Stata (Esarey and Menger, 2018). ${ }^{30}$

Regression results clustering on ex ante price plan are reported in Figure B. 1 for the absolute change in potential savings, and Figure B. 2 for the relative change in potential savings. The standard error are to some extent larger. Finally, I present results clustering on consumer. Standard errors are then drastically smaller. Results are presented in Figure B. 3 and Figure B. 4 .

[^21]Figure B.1: Regression results with 95 percent CI and standard errors clustered at ex ante price plan.

Panel A: Change in potential savings above 5 euro


Decreased potential savings


Panel B: Change in potential savings, 5 euro and less


Decreased potential savings


Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta s$ are estimated per time period. The vertical line indicates the launch of new price plans. The upper left panel shows results for consumers in which the increase in potential save is above five euro, while the upper right panel shows result for consumers with a decrease in potential save of more than five euro. The lower left panel compares consumers with an increase in potential save of five euros or less to the neutral consumers, and the lower right do the same for the consumers with decreased potential save of five euros or less. Robust standard errors clustered on consumers holding the same ex ante price plan.

Figure B.2: By size of relative change: Regression results with 95 percent CI and standard errors clustered at ex ante price plan.

Panel A: Relative change in potential savings of at least 20 percent



Panel B: Relative change in potential savings of less than 20 percent



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta$ s are estimated per time period, each consisting of three months. Hence, there are two periods before the portfolio launch and five after. The left panels show the regression results for consumers with increased potential, compared to consumers with no change in potential save. The right panels show correspondent figure for consumers with decreased potential. The vertical line indicates the launch of new price plans. Robust standard errors clustered on consumers holding the same ex ante price plan.

Figure B.3: Regression results with 95 percent CI and standard errors clustered at customer level.

Panel A: Change in potential savings above 5 euro



Panel B: Change in potential savings, 5 euro and less



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta s$ are estimated per time period. The vertical line indicates the launch of new price plans. The upper left panel shows results for consumers in which the increase in potential save is above five euro, while the upper right panel shows result for consumers with a decrease in potential save of more than five euro. The lower left panel compares consumers with an increase in potential save of five euros or less to the neutral consumers, and the lower right do the same for the consumers with decreased potential save of five euros or less. Robust standard errors clustered on consumers, 580,588 clusters.

Figure B.4: By size of relative change: Regression results with 95 percent CI and standard errors clustered at customer level.

Panel A: Relative change in potential savings of at least 20 percent



Panel B: Relative change in potential savings of less than 20 percent



Note: The figures plot regression results for the $\beta$ in Equation 3 together with 95 percent confidence intervals. The $\beta s$ are estimated per time period, each consisting of three months. Hence, there are two periods before the portfolio launch and five after. The left panels show the regression results for consumers with increased potential, compared to consumers with no change in potential save. The right panels show correspondent figure for consumers with decreased potential. The vertical line indicates the launch of new price plans. Robust standard errors clustered on consumers, 580,588 clusters.

## Chapter 4

## The Poking Effect:

Price Changes and Inertia
in the Market for Mobile Subscriptions

# The Poking Effect: Price Changes and Inertia in the Market for Mobile Subscriptions* 

Bjørn-Atle Reme ${ }^{\dagger} \quad$ Helene Lie Røhr ${ }^{\ddagger}$ Morten Sæthre ${ }^{\S}$


#### Abstract

This paper studies consumer inertia in the mobile subscription market. Particularly, we focus on the customers decision to switch to competing providers. We exploit major changes to the tariffs faced by almost 300,000 customers of a large telecom provider, to identify the effect of price changes on the propensity to switch provider. We find that the propensity to switch increases also for customers who would pay less under new tariffs, though the increase is higher for customers who would pay more. Noting that the universe of plans offered in the market was otherwise stable around the period of the tariff changes, our findings suggest the existence of choice inertia. Furthermore, we find that the propensity to switch is at its highest at time when customers are informed about the upcoming changeone month prior to the tariff changes. The strong response prior to being affected by new terms implies that active choice behavior can be induced even without learning from experience with new prices. To analyze the effect the price change has on customers attention on the choice of mobile subscription, we estimate a discrete choice model where we separate customers attention from the price change. We find that the price change more than doubles the proportion of customers being attentive.


[^22][^23]
## 1 Introduction

From time to time service providers change terms and conditions. From an economic point of view, the effect on demand from such changes is determined by the extent to which customers are made worse or better off. In markets with simple products and price structures, reoptimizing based on new prices is fairly easy. In markets where products are more complex, however, such as markets for insurance and telecommunication, optimal adjustment requires both cognitive sophistication, and information which can be costly to acquire. In practice, customers in such markets are often driven by more simplistic heuristics when determining whether or not to stay with their current provider. In this paper we argue that many consumers are passive buyers in the sense that their choice of provider is "closed" - they are not willing to take the time and effort to reoptimize unless some special event triggers them. Our paper studies how such a trigger, a sudden price change, affects the customers' propensity to leave their current service provider.

Using data from a mobile telecom provider covering 1.1 million customers over a period of 23 months, this paper presents evidence of what we label the "poking effect"-a sudden price change causes the customers to reopen a previously closed decision. The poking effect is identified by showing that in the event of an unexpected forced migration to a new price plan, the propensity to switch provider (churn) increases also for customers who are better off with the new prices. Hence, the sudden change in prices generally acts as a trigger to reopen their choice of provider. Our dataset has two features which make it particularly suited for studying consumer inertia. First, the change in monthly payments from being migrated to a new price plan varies substantially between customers, where some gain and some lose, depending on their previous price plan and usage profile. Second, customers are informed about the change two months prior to the forced migration, revealing that the largest increase in churn is driven by the information itself, and not from experience with the new price plan.

Forcing customers to migrate from their chosen price plan to a plan chosen by the
operator, may increase customers' propensity to churn, due to both the removal of customers' chosen plan, and as customers' attention to their choice of price plan is increased when they are informed about the new prices. To separate the effect of the poke on customers' attention from the effect of removing customers' current plans, we estimate a discrete choice model inspired by Hortaçsu et al. (2017). The model describe the customers' decision to churn in a two step process. First, customers become attentive or not, and second, conditional of becoming attentive, the customers choose price plan (stay on their current plan or not). Estimating the model shows that the information about the price change more than double the share of customers being attentive.

Several strands of literature are related to our paper. First, there is a literature documenting the existence and effects of limited consumer attention and choice inertia. ${ }^{1}$ Two recent papers are particularly relevant for our study: Handel (2013) and Ketcham et al. (2015) both use large datasets to shed light on important issues related to consumer behavior in markets. Handel (2013) investigates the effect of nudging in health insurance markets when there is consumer inertia. Surprisingly, he finds that nudging is likely to exacerbate adverse selection and lead to a reduction in welfare. Ketcham et al. (2015) study the relationship between the number of options and switching of the Medicare Prescription Drug Coverage plans in the US. Contrary to the choice overload theory, they find that more options lead to higher switching rates.

Second, we find that the price change increases churn also among customers who are better off in terms of expenditure. This is similar to what Ascarza et al. (2016) find. In a field experiment involving giving customers of a mobile operator expenditure reducing tariff recommendations, the intervention had unintended consequences: churn increases from a seemingly customer-friendly customer interaction.

[^24]
## 2 Data

Our study is based on data from a European mobile operator covering about 1.1 million consumers, which is the universe of the operator's postpaid customers. We have up to 23 months of billing data for each customer, from September 2013 to July 2015. ${ }^{2}$ In addition to monthly observations on mobile usage, including calling, SMS, mobile data etc., the data set contains customer characteristics such as gender, age, mobile spending, price plan, sign up date for current price plan and churn.

In an effort to simplify its subscription portfolio, the mobile operator removed 13 calling plans in May 2014, affecting about 270,000 customers. ${ }^{3}$ These customers were moved to one of two predefined plans, depending on the specific plan of the customer prior to the removal. ${ }^{4}$ An important feature of our study is that the customers were notified about the upcoming change via SMS in March, i.e. two months prior to when it was effectuated.

Our data covers the six months prior to the SMS notification, the month the SMS notifications were sent out, and the 16 months after notification (14 months after reassignment). The primary focus of our analysis is how the price change affected consumers' propensity to churn. When customers churn, we no longer have data on their mobile usage or spending. Hence, in each month we only have information on customers of the mobile operator.

The reassignment to new price plans implied a major change in the tariff structure for the affected customers. Customers on 7 of the 13 removed price plans were assigned to one new price plan, while customers of the remaining 6 price plans were assigned

[^25]to a separate, new plan. ${ }^{5}$ The assigned calling plans featured three-part tariffs-i.e., a monthly fee, an included allowance and a marginal price above the allowance - while most of the previous plans were either two-part or simple linear tariffs. For the most part, these price plans were not sold simultaneously. Hence, we see some plans strictly dominating others. With one exception, none of the removed plans had new customers during our sample period. ${ }^{6}$ The new price plans differed from the old ones both in terms of fixed fees, marginal prices, included volumes and name. If the customers did not perform an active choice, such as changing to another provider or another plan within the company, the new plan would take effect from May.

### 2.1 Identification strategy

The main purpose of our analysis is investigate the existence and severity of the poking effect - the churn caused by the information about the price change, and not how prices influence expenditures as such. To achieve this, we consider the 270,000 customers who were notified by SMS about an upcoming price change as poked, whereas the remaining customers were not poked (neither received an SMS nor a price change). The price change had a heterogeneous effect on the costs for the poked customers, depending on their usage patterns. To identify the poking effect we divide customers in groups based on how the new prices would influence expected costs, and use a difference-in-difference estimator for each subgroup of customers. The goal of this exercise is to investigate the effect on churn for customers whose costs would be unchanged, or decrease, following the price change. The effect on churn following a SMS notification about a price change which is cost neutral or cost decreasing, is interpreted as the poking effect.

[^26]
### 2.2 Impact of the price change on customers' expenditures

Since our identification strategy is based on studying different subgroups of poked customers, it is crucial to derive a measure of how the price change influences a customer's costs. We do this by estimating hypothetical costs: what the customer would have paid in the period prior the poking, had she been subject to the new price structure. We then consider a customer as better off if the new price schedule would have lowered costs, and worse off if the price change would have caused a cost increase. Based on this exercise we construct the variable Save which is the difference between the actual cost and the hypothetical cost during the six months before the notification is sent out. ${ }^{7}$ Consider the following illustration as an example: if a consumer on average paid 20 EUR per month in the pre-period, and that same consumption would have cost 10 EUR per month with the new price plan, Save equals 10 .

As Save is based on each consumer's average consumption the six months before the poking (SMS notification), its validity depends on pre-consumption being decisive in the process of decision. We believe that to be a good approach. Hortaçsu et al. (2017) and Ketcham et al. (2015) use the same logic, i.e. estimating the cost given preconsumption and new prices. Furthermore, consumption patterns of the poked consumers are stable both before and after the price change, indicating that they do not adjust their consumption in response to marginal price changes (cf. Figure A.1). Finally, since the marginal prices were reduced by the price change (cf. Table A. 1 and Table A.2), this estimate of the extent to which a customer is better or worse off, is a conservative measure.

### 2.3 Descriptive statistics

Table 1 provides summary statistics on the customers affected by the price change (Poked) and those who were not (Other). Customers' residency balances well across poked and other. ${ }^{8}$ While, on average, the two customer groups are different from each other in

[^27]terms of demographics and mobile usage. This is to be expected, since customers who have their subscription reassigned, have stayed with their price plan for a longer period prior to the reassignment.

Figure 1 shows the monthly churn rates for poked customers ${ }^{9}$ and customers on plans that were not reassigned. Before the SMS notification, the churn rate among the poked group is relatively stable and lower than other customers. Notice that although the levels are different between the groups, both groups seem to face a very similar monthly variation, indicating that they are influenced in the same way by the competitive environment. At the month of the SMS notification, however, churn among the notified plans more than triples compared to the month before, staying high for the three months from notification until reassignment. There is a noticeable increase in churn for the poked customers in the month prior to notification, due to the timing of churn registration in our data. ${ }^{10}$ In our following estimates, this will tend to overstate the churn of the poked group in the period before notification, thus giving a downward bias of the estimated increase in churn.

### 2.4 Market and competitive environment

The telecom markets in Europe are generally characterized by having two to four vertically integrated network operators and numerous service providers. The markets are national, but subject to an increasing regulatory pressure from the European Commission in the direction of building down market boundaries. Market penetration is generally very high, often exceeding 100 percent-more mobile phones than people. The firms offer both pre-paid and post-paid subscription, but the majority of European mobile users are

[^28]Table 1: Summary statistics

|  |  | Poked |  | Other |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Pre | Post | Pre | Post |
| Residency in: | 4 largest cities | $\begin{array}{r} 0.16 \\ (0.37) \end{array}$ | $\begin{array}{r} 0.16 \\ (0.36) \end{array}$ | $\begin{array}{r} 0.18 \\ (0.39) \end{array}$ | $\begin{array}{r} 0.18 \\ (0.38) \end{array}$ |
|  | City other | $\begin{array}{r} 0.08 \\ (0.27) \end{array}$ | $\begin{array}{r} 0.08 \\ (0.27) \end{array}$ | $\begin{array}{r} 0.09 \\ (0.29) \end{array}$ | $\begin{array}{r} 0.09 \\ (0.28) \end{array}$ |
|  | Urban other | $\begin{array}{r} 0.04 \\ (0.19) \end{array}$ | $\begin{array}{r} 0.03 \\ (0.16) \end{array}$ | $\begin{array}{r} 0.01 \\ (0.11) \end{array}$ | $\begin{array}{r} 0.01 \\ (0.09) \end{array}$ |
|  | Village | $\begin{array}{r} 0.47 \\ (0.50) \end{array}$ | $\begin{array}{r} 0.49 \\ (0.50) \end{array}$ | $\begin{array}{r} 0.45 \\ (0.50) \end{array}$ | $\begin{array}{r} 0.46 \\ (0.50) \end{array}$ |
|  | Other | $\begin{array}{r} 0.25 \\ (0.43) \end{array}$ | $\begin{array}{r} 0.25 \\ (0.43) \end{array}$ | $\begin{array}{r} 0.26 \\ (0.44) \end{array}$ | $\begin{array}{r} 0.26 \\ (0.44) \end{array}$ |
| Age |  | $\begin{array}{r} 61.78 \\ (14.52) \end{array}$ | $\begin{array}{r} 62.78 \\ (14.07) \end{array}$ | $\begin{array}{r} 47.92 \\ (14.25) \end{array}$ | $\begin{array}{r} 48.51 \\ (14.19) \end{array}$ |
| Female, share |  | $\begin{array}{r} 0.41 \\ (0.49) \end{array}$ | $\begin{array}{r} 0.42 \\ (0.49) \end{array}$ | $\begin{array}{r} 0.50 \\ (0.50) \end{array}$ | $\begin{array}{r} 0.51 \\ (0.50) \end{array}$ |
| Churn, percent |  | $\begin{array}{r} 1.08 \\ (10.32) \end{array}$ | $\begin{array}{r} 1.61 \\ (12.60) \end{array}$ | $\begin{array}{r} 1.22 \\ (10.96) \end{array}$ | $\begin{array}{r} 1.04 \\ (10.15) \end{array}$ |
| Plan change, percent |  | $\begin{array}{r} 0.39 \\ (6.23) \end{array}$ | $\begin{array}{r} 8.59 \\ (28.03) \end{array}$ | $\begin{array}{r} 4.46 \\ (20.64) \end{array}$ | $\begin{array}{r} 4.61 \\ (20.97) \end{array}$ |
| Save |  | $\begin{array}{r} -6.44 \\ (9.64) \end{array}$ | $\begin{array}{r} -6.00 \\ (9.73) \end{array}$ | $\begin{array}{r} -10.07 \\ (19.36) \end{array}$ | $\begin{array}{r} -10.13 \\ (19.23) \end{array}$ |
| Fixed fees |  | $\begin{array}{r} 1.41 \\ (2.70) \end{array}$ | $\begin{gathered} 13.19 \\ (6.75) \end{gathered}$ | $\begin{gathered} 22.66 \\ (9.61) \end{gathered}$ | $\begin{aligned} & 25.12 \\ & (8.63) \end{aligned}$ |
| Variable fees |  | $\begin{array}{r} 8.99 \\ (11.86) \end{array}$ | $\begin{array}{r} 8.16 \\ (12.54) \end{array}$ | $\begin{array}{r} 18.48 \\ (18.94) \end{array}$ | $\begin{array}{r} 15.80 \\ (19.16) \end{array}$ |
| Voice minutes |  | $\begin{array}{r} 83.13 \\ (117.02) \end{array}$ | $\begin{array}{r} 99.37 \\ (141.14) \end{array}$ | $\begin{array}{r} 219.03 \\ (258.97) \end{array}$ | $\begin{array}{r} 230.80 \\ (287.45) \end{array}$ |
| SMS |  | $\begin{array}{r} 28.63 \\ (57.88) \end{array}$ | $\begin{array}{r} 30.81 \\ (65.05) \end{array}$ | $\begin{array}{r} 112.17 \\ (146.68) \end{array}$ | $\begin{array}{r} 115.29 \\ (166.68) \end{array}$ |
| Megabytes |  | $\begin{array}{r} 14.83 \\ (187.57) \end{array}$ | $\begin{array}{r} 56.15 \\ (387.27) \end{array}$ | $\begin{array}{r} 443.08 \\ (979.31) \end{array}$ | $\begin{array}{r} 821.32 \\ (1615.39) \end{array}$ |
| No. of customers |  | 284,627 | 266,830 | 665,207 | 618,669 |

[^29]Figure 1: Churn rates


Note: The figure shows monthly churn rate in percent separately for poked customers (black line) and not poked customers (gray line). The time from poking to customers actually were reassigned to new price plans is indicated by the gray area.
post-paid users, which implies that they subscribe to their telecom provider's service and pay bills on a regular basis. ${ }^{11}$ Since our identification strategy is based on utilizing a sudden price change, it is important to understand the competitive dynamic: how and whether competitors might respond. In this section we present both how firms compete for customers and evidence that competitor response is not likely to be of concern.

An important feature of the market dynamics of telecommunications is the existence of both list prices and specialized offers given to customers. Prices and advertising which are public are often referred to as "above the line offers", while offers given in private to customers as part of special campaigns are referred to as "below the line offers". The extent of "below the line offers" in a market typically depends on the intensity of competition and national regulation. Below the line offers can be given both to existing customers and customers of other suppliers. A supplier has much more information about

[^30]its current customers than those of competitors. This difference in level of information makes the nature of below the line very different between these two groups: offers to existing customers can be tailored and specialized, while this is not possible for potential customers. The market from which we have data has a relatively low extent of "below the line offers" given to customers from competing suppliers.

This dynamic, above and below the line pricing, is important to understand in relation to how competitors might respond to the price change which we study. Competitor response is a concern since it could drive customer churn, and thereby weaken our identification. We believe that competitor response is not likely to be of concern. First of all, with regards to above the line prices, the relevant competitors did not change their prices in this period. Second, with regards to below the line prices, the customers affected by the price change constitute a selected group of customers who are not identifiable by competing providers wanting to approach them with an offer. We have also discussed this price change with the responsible managers to ask whether they were aware of any below the line campaigns from competitors in response to the price change. Managers typically have very detailed knowledge about what competitors are doing through real-time customer feedback. The responsible managers were not aware of any campaigns started as a direct response to the price change.

## 3 Estimating the poking effect

Due to time and attention constraints, many consumer decisions are based on habit. Past purchase behavior is repeated without much thinking. This pattern of repeating past behavior goes on until something special happens or catches the customer's attention, a poke, which forces them to reconsider their previous decision. Put differently, their choice of service provider is "closed", unless given a reason to reconsider, i.e. "reopen" the decision, and make an overall assessment of the offers available in the market. There are several kinds of events which could poke a customer to "reopen" choice of provider,
such as advertising campaigns, an unexpectedly high bill or a sudden price change. In the remaining part of this section, we estimate the "poking effect" from the SMS notification regarding a price change.

### 3.1 The difference-in-difference estimation

From Figure 1 we saw that there was a strong increase in churn following the change in prices. This should not come as a surprise since a large proportion of the customers experienced an increase in expected expenditure. Given that we are interested in the poking effect from the notification, we are particularly interested in studying the customers whose expected cost would be unchanged or decrease. In order to study this we estimate a difference-in-difference model where we split customers into discrete groups of Save, the estimate of how the new prices influences each customer's expenditures. This model can inform us of the treatment effect of the price change on churn for each sub-group.

We start out by defining four time periods: before, during and two after periods. Before contains the six months prior to the treated customers are notified about the price change. During covers the months March to May 2014, where March is when the SMS notification was sent out, and May is the month customers are reassigned. The two After periods, split the remaining months in two, eight in each period. Our goal is to investigate the extent to which the change in expected expenditure can explain the increase in churn following the price change, with particular focus on the during period. For expositional ease we ignore the after periods in the following presentation; however, they are included in the estimation.

We then split customers into 12 categories, dependent of their change in expenditures, i.e. change in Save. For customers who were not poked, save measures the savings they would have obtained if they would have been reassigned or had they chosen the new price plan themselves. For each category of Save we estimate the following model:

$$
\begin{equation*}
\text { churn }=\alpha+\gamma_{1} d_{\text {during }}+\gamma_{2} d_{\text {poked }}+\gamma_{3} d_{\text {during }} d_{\text {poked }}+\boldsymbol{x}^{\prime} \beta+\epsilon, \tag{1}
\end{equation*}
$$

where $d_{\text {during }}$ is dummy for the during period, i.e. the months following the SMS notification. $d_{\text {poked }}$ is a dummy which is equal to one if the customer received a SMS notification. ${ }^{12}$ $\boldsymbol{x}$ is a vector of controls, containing age, gender and area of residence.

We are particularly interested in $\gamma_{3}$, as it measures the change in churn for the "poked"-group in the months following the SMS notification, compared to before the price change. For our estimates to be valid, we need that the assumption of common trend holds within each savings group. To a large degree, common trends seem to hold for each group (see Figure A. 3 in the Appendix).

### 3.2 Estimation results

Figure 2 shows the estimated increase in churn, $\gamma_{3}$ from Equation 1, i.e. the increase in churn in the during period compared to the before period for the poked customer per category of predicted Save. Not surprisingly, we see that the increase in churn is larger the lower is Save. However, the increase in churn is substantial also for customers who are predicted to be unaffected or better off under the new price plan. The customers who are predicted to save from the new price plans increase their churn with 0.5 to 1 percentage points, which amounts to an increase of $50-80$ percent of the before churn rate. ${ }^{13}$

Having established the existence of a poking effect in the previous section, we would like to analyze potential causes behind it. We start with an explanation which we can rule out without further analysis: learning from experience, which implies that customers decide to churn based on learning how the new prices affect them. This explanation can be ruled out because the poking effect we identify is at its strongest immediately after notification, i.e. before the customer has had the time to experience new prices. Hence, the timing aspect of the effect rules out this explanation.

Surprisingly, we do not find evidence of heterogeneity within areas predicted from

[^31]Figure 2: Estimated churn increase for the poked in during period by predicted save categories


Note: The figure shows estimated churn increase, in percentage points, from the before to the during period ( $\gamma_{3}$ ) for different intervals of predicted savings categories with 95 percent confidence intervals indicated by errors bars. Robust standard errors clustered at the individual's choice of price plan before the poke, i.e. a combination of price plan and the tenure on that price plan, 3,089 clusters.
literature; salience of specific prices (cf. Grubb, 2015a; Bordalo et al., 2012; Gabaix and Laibson, 2006) ${ }^{14}$ or salience of the size of a bill (cf. Grubb, 2015b). ${ }^{15}$ We find, on the other hand, large heterogeneity in the churn increase if we split the customers by age, cf.

Figure A.4. Younger customers are more prone to churn over all, and respond more to

[^32]the price change.
Our results are in line with at least one explanation which cannot be ruled out: Customers generally believe that when their telecom provider changes its prices, it is to the customers' disadvantage. Given the combination of high product complexity and that service providers seek to increase profits, it seems both likely and rational that customers are generally skeptical regarding how price changes will affect them. In other words, when presented with new prices, the customer automatically assumes that expenditures will increase, and considers finding an alternative provider.

Being moved to a new price plan causes an increase in churn. In fact, some of the increase occurs regardless of whether the customers are better or worse off with the new plans, which is a clear indication that moving customers increases their attention. At the time of the poking, competitors offer price plans which dominates the plans customers hold. ${ }^{16}$ Observing that customers, which have become more attentive, churn more, is in that respect no surprise.

We have labeled the increase in churn a "poking effect", but it is merely a description of behavior. For managers, knowing about this effect is valuable, as it helps understand potentially unintended consequences of making changes to the price portfolio. But, these results do not give insight into the deeper causes of the "poking effect". In the following section we discuss this effect in more detail by the use of a simple model.

## 4 A model of consumer attention and choice

In the previous section we established that there was a significant and substantial increase in churn following the notification, also for customers who were equally well or better off from the new price structure. We interpreted it as a "poking effect", an increase in churn caused by a reduction in consumer inertia. In this section we build a model inspired by Hortaçsu et al. (2017), which allows us to separate the effect of the poke on customer

[^33]attention from the effect of removing customers' current plans. The reasoning behind the model structure is based on the notion that a customer can either be attentive or inattentive. An inattentive customer is on "autopilot", i.e. automatically repeating past behavior without further thought. An attentive customer is involved in the sense of actively optimizing by considering alternative offers in the market. Using this structure, a churn event is a combination of becoming attentive, i.e. considering alternative offers, and choosing a plan from a different provider. At the same time there will be customers who are attentive, but decide not to churn. Hence, the effect on attention is higher than the effect on churn.

Our model can be described as a two-stage process of customer choice. In stage 1 the customer either becomes attentive or stays inattentive. In stage 2, conditional on being attentive, the customer chooses between the plans currently offered in the market. Thus, churn happens when the consumer is both attentive, and prefers one of the plans offered by competing providers over the plans offered by the current provider. Stage 2 can be interpreted as an "implicit brand effect". Customers whom are attentive, and still not churn in the presence of less expensive alternatives in the market, are willing to pay a brand mark-up.

When customers are informed about the price change, their propensity to churn increases, already two months before the price change is effectuated. This behavior is consistent with customers behaving forward-looking in the following way: Imagine making a choice knowing that, due to inattention, there is only a certain probability that you can change that choice at any point in time. When you learn that the payoff of one of the choices will change in the future, this should be factored into your current decision. This type of forward-looking behavior will imply that the consumers in our data increase their propensity to churn when they are informed about a upcoming price change, even though they would have preferred their initial choice of price plan.

### 4.1 Model specification

Formally, we estimate a model of the joint probability of being attentive and the optimal choice of plan conditional on being attentive. Let $p_{i t}^{A}$ be the probability that customer $i$ is attentive in month $t$, and let $p_{i j t}^{C}$ be the probability that plan $j \in \mathcal{J}_{t}$ is optimal, where $\mathcal{J}_{t}$ is the set of plans offered by all firms in month $t$. Let $y_{i t}$ denote customer $i$ 's choice of plan in month $t$. The probability of observing a choice $y_{i t} \neq y_{i, t-1}$ is $p_{i t}^{A} p_{i t}^{C}\left(d_{t}\right)$, while the probability of observing $y_{i t}=y_{i, t-1}$ is $p_{i t}^{A} p_{i t}^{C}\left(d_{t}\right)+\left(1-p_{i t}^{A}\right)$. In the case where a customer changes plan from one period to the next, the customer was by definition attentive, while the customer repeats the previous choice either if he is attentive and it is the optimal choice or if he is inattentive. The structure of the model is equivalent to the one utilized by Hortaçsu et al. (2017) to study consumer inertia in the Texas retail electricity market. Similar to them, we take a reduced-form approach to modeling $p^{A}$, specifying it as a logit depending on age, gender, and centrality of area of residence of the customer, in addition to time dummies interacted with treatment status of the customer, i.e.,

$$
\begin{gather*}
p_{i t}^{A}=\frac{e^{f_{A}\left(W_{i}, d_{p o k e d}, t\right)}}{1+e^{f_{A}\left(W_{i}, d_{\text {poked }, t}\right)}} \\
f_{A}\left(W_{i}, d_{p o k e d}, t\right)=W_{i}^{\prime} \eta+\gamma d_{\text {poked }}+\sum_{\tau=1}^{T} \lambda_{\tau} d_{\tau}+\sum_{\tau=1}^{T} \delta_{\tau} d_{\tau} \cdot d_{\text {poked }}, \tag{2}
\end{gather*}
$$

where $W_{i}$ is the vector of individual characteristics listed above, $d_{\tau}$ is an indicator for month $\tau$ of the sample, and $d_{\text {poked }}$ is an indicator for customers who are on a plan that will be moved prior to notification (in March) or who was on such a plan when notifications of the change was sent (regardless of whether they later switch plans). The notification sent out by the firm creates a source of variation. We argue that when we condition on the (potential) change in payoff from staying with the current choice at the time when the customer learns of the upcoming change, the notification affects customers' attention separately from their choice behavior.

We let the flow utility of customer $i$ from plan $j$ in month $t$ be given by

$$
\begin{equation*}
v_{i j t}=\alpha p_{i j t}+\sum_{f} \kappa_{f} d_{j f}, \tag{3}
\end{equation*}
$$

where $p_{i j t}$ is the cost of the plan to the customer and $d_{j f}$ are indicators for plan $j$ being sold by firm $f$. The pattern we find in our reduced-form analysis is consistent with customers being inattentive and forward-looking, and we therefore chose to model them as taking into account future inattention when being attentive and making an active choice. The customer will expect the duration until the next time he makes an active choice to be the reciprocal of the attention probability $1 / p_{i t}^{A}$, and the relevant value to the customer when deciding between the plans, disregarding discounting, is $V_{i j t}=v_{i j t} / p_{i t}^{A} .{ }^{17}$ Under regular circumstances, when no change in the contract structure of any plans is expected, the utility-maximizing choice in the current period (given by $v_{i j t}$ ) and the expected flowutility until the next active choice (given by $V_{i j t}$ ) coincides. The distinction will only be relevant for customers who are informed of the upcoming change in contract and who become attentive before the change is enacted. Even if their current plan is optimal among the plans offered in the market at that time, these customers might decide to choose a plan that is worse than their current to avoid being stuck with the new conditions due to inattention.

Since the notification of the change comes two months prior the change itself, customers who become attentive at this point will be able to get two months on the current plan before their conditions change. Letting $t_{C}$ denote the month of the change, the value

[^34]of choosing the current plan will, for these customers, be
$$
V_{i, y_{i, t_{C}-3}, t_{C}-2}=\left[1+\left(1-p_{i, t_{C}-2}^{A}\right)\right] u_{i, y_{i, t_{C}-3}, t_{C}-2}+\frac{\left(1-p_{i, t_{C}-2}^{A}\right)^{2}}{p_{i, t_{C}-2}^{A}} u_{i, y_{i, t_{C}-3}, t_{C}},
$$
where $t_{C}$ denotes the month of the change itself, $y_{i, t_{C}-3}$ denotes the current choice (seen from the perspective of two months before the change), $u_{i, y_{i, t_{C}-3}, t_{C}-2}$ is the current payoff on the current plan, and $u_{i, y_{i, t_{C}-3}, t_{C}}$ is the payoff under the contract terms after the change. The first term is the expected value of one "voluntary" month on the current plan and an additional month on this plan due to inattention. The second term is the expected value from not making an active choice until the new contract terms take effect and being stuck with the new prices due to inattention. Similarly, for a customer who is notified and is attentive one month before the change, the value of choosing the current plan is
$$
V_{i, y_{i, t_{C}-2}, t_{C}-1}=u_{i, y_{i, t_{C}-2}, t_{C}-1}+\frac{1-p_{i, t_{C}-1}^{A}}{p_{i, t_{C}-1}^{A}} u_{i, y_{i, t_{C}-2, t_{C}}}
$$
where there is now one month actively chosen on the current plan, before inattention which might make the consumer being stuck with the new terms with a probability $1-p_{i, t_{C}-1}^{A}$ in each period.

We model the full expected utility of choosing plan $j$ as

$$
u_{i j t}=V_{i j t}+\epsilon_{i j t}
$$

where $\epsilon_{i j t}$ is a standard IID Gumbel-distributed (extreme value type I) random utility term. Thus, the choice probabilities (conditional on attention) are given by

$$
\begin{equation*}
p_{i j t}^{C}=\frac{e^{V_{i j t}}}{\sum_{k \in \mathcal{J}_{t}} e^{V_{i k t}}} \tag{4}
\end{equation*}
$$

The likelihood of observing customer $i$ 's choice $y_{i t}$ in period $t$ is then

$$
L_{i t}=p_{i t}^{A} p_{i, y_{i t}, t}^{C}+\left(1-p_{i t}^{A}\right) \nVdash\left(y_{i, t-1}=y_{i t}\right),
$$

where the last part corresponds to the probability that a repeated choice is due to inattention.

The log likelihood of the sample is

$$
\ln \mathcal{L}=\sum_{i} \sum_{t} \ln L_{i t},
$$

which we maximize with respect to the model parameters. Currently, we estimate our model on a random sample of 10,000 individual customers.

After estimation, we can calculate the probability of churn as follows: Let $\mathcal{D}_{t}$ denote the set of plans offered by competing providers in month $t$. Choosing a plan from this set means that the customer churns. The probability of churning is thus given by

$$
\operatorname{Pr}_{i t}^{C}=p_{i t}^{A} \cdot \sum_{j \in \mathcal{D}_{t}} p_{i j t}^{C},
$$

which we can use to assess the model against what we observe in the data. Note that our choice model does not directly target churn, and the probability of churn conditional on attention $\left(\sum_{j \in \mathcal{D}_{t}} p_{i j t}^{C}\right)$ will depend on how well the model approximates consumer choice over the full set of contracts.

### 4.2 Results from model estimation

Figure 3 presents the main results from stage 1. ${ }^{18}$ There are several interesting things to note from the figure. First, the estimated share of customers who are attentive in a month is fairly low, around 5 percent. Second, the text message which informed about an upcoming price change - the poke - had a strong effect on customers' attention. The share of consumers becoming attentive more than doubles following the poke.

Note also that attention varies strongly with age, the base attention rate being nine percent for customers between 20 and 30 years old and four percent for customers above

[^35]Figure 3: Predicted effect of poke on attention


Note: The figure shows the estimated levels of attention from the model, in percent of customers being attentive. The black line indicates the poked customers, while the gray line indicated those not poked. The model allows attention to vary separately by poked and non-poked customers in each month, in addition to demographics and mobile usage pattern.

80 years (see Figure 4). We also find statistically significant, though relatively modest effects of being more or less intensive in use of calls, text and data. The results suggest that customers who on average use more calling and texts are less attentive, while the opposite is true for data use. Since the variables are standardized to unit-variance, the estimated coefficients imply that the impact (in log-odds) of a one standard deviation increase in usage, is equivalent to one half to one third of the impact of going from 20 to 30 years of age.

Using our model estimates we may predict churn. This exercise serves as a validation that our dynamic model provides a good description of actual behavior. The result from predicting churn compared to observed churn in the random sample of 10,000 individuals used for estimation is presented in Figure 5. Though the predicted level of churn is about 0.5 percentage points lower than actual levels for the poked customers and predicted levels are about 0.25 percentage points higher than actual levels for the non-poked customers, the estimated changes over time closely matches the observed pattern.

There is also an interesting insight from the estimation of stage 2 related to the

Figure 4: Attention by age


Note: The figure shows the average predicted levels of attention, in percent of customers, from the estimated model across 10-year age groups (left-side of interval provided) for the period prior to the poke.

Figure 5: Predicted effect of poked on churn


Note: The figures show the predicted effect of the poke on churn, in percent, for the poked customers (black line) and those not poked (gray line). Panel (a) shows the implied rate of churn from the model, while panel (b) shows the observed rate of churn in the subsample used for estimation. The model allows attention to vary separately by poked and non-poked customers in each month, in addition to demographics and mobile usage pattern.
"implicit brand effect". This effect can be thought of as the average monetary value of sticking to the current provider instead of churning. Put differently, for many customers
there are cheaper options available in the market which are not chosen to the extent we should expect from a simple model focusing on costs of usage. Hence, there are other aspects of the providers, perhaps related to quality of service, emotional attachment, or habits which hinders churn.

## 6 Concluding remarks

Summarizing the results, we find a significant and strong increase in customer churn following a notification about a future price change. This effect also holds for customers whose expenditures become lower with the new prices. This we interpret as a poking effect: the notification about the price change causes many customers to wake up and start searching for alternative offers. Our results are in line with Ascarza et al. (2016), who also finds that giving offers to consumers which lowers their expenditure can backfire and increase churn. The data does not allow us to reveal the mechanism causing the poking effect, but there is at least one obvious candidate which cannot be ruled out: when an operator changes its prices, customers by default believe the change is to their disadvantage. And on average, the customers are right, the average customer were worse off. In markets with complex prices and uncertain consumption, customers are likely to base their decisions on simple heuristics such as: if the operator changes the price, my expenditures will most likely increase.

Estimating a discrete choice model allows us to estimate the extent of customer attention, and the effect on attention from the poke: on average about six percent of the customers are attentive in a given month leading up to the price change, and the poke approximately doubles the proportion of attentive customers. This result has policy relevance for e.g. consumer authorities aiming to decrease inertia in a similar market.

Our results have managerial implications for service providers, in particular those with a complex price structure. Managers should be aware that changes in terms and conditions could cause an increase in churn, not only for customers who are worse off, but
also for those who are better off. This poking effect can to some extent be mitigated by clearly explaining the customers that the change is to their advantage, when it actually is to their advantage. However, and as shown by Ascarza et al. (2016), it is not necessarily sufficient - regardless of whether better or worse off, service provider interactions can trigger search for alternative offers from competing providers.

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## Appendix A: Supplementary analyses

Figure A.1: Average consumption among poked customers


Note: The figures shows the average monthly usage of Mega bytes (left panel), calling minutes (mid panel) and SMS (right panel). The vertical dashed line indicates the moving date, i.e. the date the customers face new prices.

Table A.1: Poked plan overview migration 1

| Plan | Prices |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
|  | Fixed fee | Minutes <br> included | Minute price <br> above incl. | SMS price <br> above incl. | MB price |
| Old plan A | 8.9 | 60 | 0.09 | 0.07 | 1.25 |
| Old plan B | 4.9 | 20 | 0.18 | 0.07 | 1.25 |
| Old plan C | 4.9 | 0 | 0.05 | 0.05 | 1.25 |
| Old plan D | 4.9 | 0 | 0.09 | 0.07 | 1.25 |
| Old plan E | 0 | 0 | 0.05 | 0.05 | 1.25 |
| Old plan F | 0 | 0 | 0.05 | 0.05 | 1.25 |
| Old plan G | 5.9 | 0 | 0.10 | 0.07 | 1.25 |
| New plan 1 | 12.9 | 100 | 0.05 | 0.05 | 1.0 |

Note: The table gives an overview over prices of seven old plans (old plan A-G) and the new plan (New plan 1) that these seven old plans are moved to. Standardized currency.

Table A.2: Poked plan overview migration 2

| Plan | Prices |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
|  | Fixed fee | SMS <br> included | Minute price <br> above incl. | SMS price <br> above incl. | MB price |
| Old plan H | 2.9 | 0 | 0.07 | 0.04 | 1.25 |
| Old plan I | 0 | 0 | 0.09 | 0.07 | 1.25 |
| Old plan J | 6.9 | 0 | 0.16 | 0.07 | 1.25 |
| Old plan K | 0 | 0 | 0.05 | 0.05 | 1.25 |
| Old plan L | 0 | 0 | 0.05 | 0.05 | 1.25 |
| Old plan M | 0 | 0 | 0.04 | 0.04 | 0.50 |
| New plan 2 | 9.90 | 100 | 0.05 | 0.05 | 1.0 |

Note: The table gives an overview over prices of six old plans (old plan H-M) and the new plan (New plan 2) these six old plans are moved to. Standardized currency.

Figure A.2: Churn rates using actual churn date


Note: The figure shows the churn rate separately for poked customers and not poked customers. The time from poking to actual price change is indicated as a gray area.

Figure A.3: Churn rates within savings categories


Note: Each panel shows the churn rate for a specific category of savings, separately for customers who are on plans to be removed and customers on all other plans. TThe time from poking to actual price change is indicated as a gray area.

Figure A.4: Churn rates within age categories


Note: The time from poking to actual price change is indicated as a gray area.

Table A.3: Overview of main competitor prices at time of poking

| Plan | Prices |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  | Fixed | Min. price <br> above incl. | SMS price <br> above incl. | Incl. <br> MB | Incl. <br> min | Incl. |
|  | SMS |  |  |  |  |  |
| Comp. 1: plan A | 20 | 0 | 0 | 1000 | unlimited | unlimited |
| Comp. 1: plan B | 30 | 0 | 0 | 5000 | unlimited | unlimited |
| Comp. 1: plan C | 10 | 0.04 | 0.04 | 150 | 150 | 150 |
| Comp. 1: plan D | 40 | 0 | 0 | 8000 | unlimited | unlimited |
| Comp. 2: plan A | 30 | 0 | 0 | 3000 | unlimited | unlimited |
| Comp. 2: plan B | 20 | 0 | 0 | 500 | unlimited | unlimited |
| Comp. 2: plan C | 40 | 0 | 0 | 6000 | unlimited | unlimited |
| Comp. 2: plan D | 50 | 0 | 0 | 8000 | unlimited | unlimited |
| Comp. 3: plan A | 5 | 0.04 | 0.03 | 0 | 0 | 0 |
| Comp. 3: plan B | 20 | 0 | 0 | 1000 | unlimited | unlimited |
| Comp. 3: plan C | 30 | 0 | 0 | 5000 | unlimited | unlimited |
| Comp. 3: plan D | 10 | 0.04 | 0.04 | 150 | 150 | 150 |
| Comp. 4: plan A | 20 | 0 | 0 | 1000 | unlimited | unlimited |
| Comp. 4: plan B | 30 | 0 | 0 | 5000 | unlimited | unlimited |
| Comp. 5: plan A | 5 | 0.04 | 0.04 | 0 | 0 | 0 |
| Comp. 5: plan B | 40 | 0 | 0 | 6000 | unlimited | unlimited |
| Comp. 6: plan A | 30 | 0 | 0 | 3000 | unlimited | unlimited |
| Comp. 6: plan B | 25 | 0 | 0 | 1000 | unlimited | unlimited |
| Comp. 6: plan C | 15 | 0.05 | 0.05 | 200 | 200 | 200 |

Note: The table gives an overview over the main offers by the main competitors at the time of the poke (when customers were informed about the price change). The main competitors do not make any major price changes in the next three month period.

Table A.4: Results controlling for save categories

| Predicted savings categories | $(1)$ | $(2)$ | $(3)$ |
| :--- | ---: | ---: | ---: |
| Save (-50,-15] | $3.988^{* * *}$ | $3.990^{* * *}$ | $3.390^{* * *}$ |
| Save (-15,-10] | $(0.178)$ | $(0.177)$ | $(0.149)$ |
|  | $3.771^{* * *}$ | $3.771^{* * *}$ | $3.522^{* * *}$ |
| Save (-10,-7.5] | $(0.120)$ | $(0.118)$ | $(0.093)$ |
|  | $2.941^{* * *}$ | $2.916^{* * *}$ | $2.802^{* * *}$ |
| Save (-7.5,-5] | $(0.133)$ | $(0.131)$ | $(0.117)$ |
|  | $2.131^{* * *}$ | $2.103^{* * *}$ | $2.096^{* * *}$ |
| Save (-5,-2.5] | $(0.121)$ | $(0.120)$ | $(0.106)$ |
|  | $1.385^{* * *}$ | $1.362^{* * *}$ | $1.380^{* * *}$ |
| Save (-2.5,0] | $(0.104)$ | $(0.103)$ | $(0.093)$ |
|  | $1.008^{* * *}$ | $0.987^{* * *}$ | $0.994^{* * *}$ |
| Save (0,2.5] | $(0.117)$ | $(0.116)$ | $(0.107)$ |
|  | $0.882^{* * *}$ | $0.867^{* * *}$ | $0.881^{* * *}$ |
| Save (2.5,5] | $0.117)$ | $(0.115)$ | $(0.109)$ |
|  | $0.731^{* * *}$ | $0.712^{* * *}$ | $0.726^{* * *}$ |
| Save (5,7.5] | $(0.130)$ | $(0.129)$ | $(0.123)$ |
| Save (7.5,10] | $0.632^{* * *}$ | $0.630^{* * *}$ | $0.635^{* * *}$ |
|  | $(0.141)$ | $(0.140)$ | $(0.136)$ |
| Save (10,15] | $0.917^{* * *}$ | $0.898^{* * *}$ | $0.932^{* * *}$ |
|  | $(0.235)$ | $(0.233)$ | $(0.224)$ |
| Save (15,50] | $0.507^{* * *}$ | $0.494^{* * *}$ | $0.541^{* * *}$ |
|  | $(0.171)$ | $(0.169)$ | $(0.163)$ |
| Demographics | $0.525^{* *}$ | $0.510^{* *}$ | $0.521^{* *}$ |
| Demogr. interact with treatment | $(0.216)$ | $(0.213)$ | $(0.204)$ |

Note: The table shows estimation results the churn increase in the during period per predicted savings category, i.e. $\gamma_{3}$ in Equation 1. Model (1) reports on estimation results without any control variables. In model (2) we add controls for age, gender and place of residence, while in model (3) we also interact the demographics with treatment (being poked and time periods). Robust standard errors clustered on consumers' choice of price plan before the poke, i.e. a combination of price plan and tenure on that plan, 3,089 clusters. ${ }^{*} p<0.10,^{* *} p<0.05,{ }^{* * *} p<0.01$

Table A.5: Model estimation results

|  |  |  |
| :--- | ---: | ---: |
|  | coef | std.err |
| Stage 1: Attention parameters |  |  |
| Intercept | -3.30 | 0.11 |
| Residency: Four largest city | 0.14 | 0.08 |
| Residency: Urban | 0.00 | 0.08 |
| Residency: Village | 0.01 | 0.08 |
| Residency: Unknown | 1.31 | 0.15 |
| Age: 30-40 | -0.24 | 0.08 |
| Age: 40-50 | -0.44 | 0.08 |
| Age: 50-60 | -0.57 | 0.08 |
| Age: 60-70 | -0.74 | 0.08 |
| Age: 70-80 | -0.80 | 0.10 |
| Age: above 80 | -1.15 | 0.14 |
| Poked | -0.53 | 0.11 |
| Period 1 | -0.11 | 0.07 |
| Period 2 | -0.06 | 0.07 |
| Period 3 | -0.03 | 0.07 |
| Period 4 | 0.10 | 0.07 |
| Poked in period 1 | 0.13 | 0.15 |
| Poked in period 2 | 0.79 | 0.15 |
| Poked in period 3 | 1.40 | 0.14 |
| Poked in period 4 | 1.09 | 0.15 |
| Female | -0.03 | 0.04 |
| Voice minutes | -0.08 | 0.02 |
| SMS | -0.08 | 0.02 |
| Megabytes | 0.10 | 0.02 |
| Stage 2: Choice parameters |  |  |
| Expenditures | -0.06 | 0.00 |
| Other | -1.69 | 0.07 |
| Current provider | 0.61 | 0.05 |
|  |  |  |

[^36]
## Appendix B: Dynamic model and choice probabilities

We can define the ex ante (integrated) value function as

$$
\begin{align*}
\bar{V}(d, \mathcal{D}) & =\mathbb{E} V(d, \mathcal{D}, a, \epsilon)=\sum_{a} \int V(d, \mathcal{D}, a, \epsilon) p_{a}(a) g_{\epsilon}(\epsilon) \mathrm{d} \epsilon \\
& =\lambda \ln \left(\sum_{d^{\prime} \in \mathcal{D}} \exp \left\{u\left(d^{\prime}\right)+\beta \bar{V}\left(d^{\prime}, \mathcal{D}^{\prime}\right)\right\}\right) \\
& +(1-\lambda)\left\{u(d)+\beta \bar{V}\left(d, \mathcal{D}^{\prime}\right)\right\}, \tag{5}
\end{align*}
$$

where $\lambda \equiv p_{a}(1)$, i.e., the probability of being attentive. The log of summed exponentials is the well-known expression for expected utility when choosing among several options with additive extreme value type 1 random utility terms, also known as the inclusive value. Let $I_{\mathcal{D}}$ denote the inclusive value from choice set $\mathcal{D}$. When the consumer does not expect any changes in the set of available plans, i.e., $\mathcal{D}=\mathcal{D}^{\prime}$, we can express a partial solution to the ex ante Bellman equation as

$$
\begin{equation*}
\bar{V}(d, \mathcal{D})=\frac{\lambda}{1-\beta(1-\lambda)} I_{\mathcal{D}}+\frac{1-\lambda}{1-\beta(1-\lambda)} u(d) \tag{6}
\end{equation*}
$$

where the common denominator reflects the possibility of staying inattentive in any number of consecutive periods adjusted for discounting. Note that only the second term depends on the endogenous state variable $d$, where $d$ reflects the choice made in the last attentive period. When the consumer becomes attentive, the previous choice is not important to the consumer, only the future possibility of repeating the current choice due to inattention.

In periods where the consumer is attentive, the value of a choice $d$ net of $\epsilon$ is

$$
\begin{equation*}
v(d)=u(d)+\beta \bar{V}\left(d, \mathcal{D}^{\prime}\right) \tag{7}
\end{equation*}
$$

which defines the (conditional) choice probabilities through

$$
\begin{align*}
\operatorname{Pr}(d \mid \mathcal{D}) & =\operatorname{Pr}(v(d)+\epsilon(d) \geq v(k)+\epsilon(k), \forall k \in \mathcal{D} \backslash d) \\
& =\frac{e^{v(d)}}{\sum_{k \in \mathcal{D}} e^{v(k)}} . \tag{8}
\end{align*}
$$

In the case where the consumer does not expect any changes in the choice set, and we set $\beta=1$, we can insert for Equation (6) in (7), which simplifies to

$$
\begin{equation*}
v(d)=\frac{1}{\lambda} u(d)+I_{\mathcal{D}} \tag{9}
\end{equation*}
$$

where we see that $I_{\mathcal{D}}$ is common to all choices, and will thus not affect the choice probabilities:

$$
\operatorname{Pr}(d \mid \mathcal{D})=\frac{e^{\frac{1}{\lambda} u(d)}}{\sum_{k \in \mathcal{D}} e^{\frac{1}{\lambda} u(k)}}
$$

Only the current flow utility of each plans is involved in the decision when consumers expect the supply of plans to be stable. The reciprocal of $\lambda$ reflects the expected time until the consumer is attentive again, i.e., the expected time being stuck with the chosen plan without being able to reoptimize. Note that $\beta=1 \mathrm{implies}$ that $I_{\mathcal{D}}$ is non-finite, and should thus be interpreted as a notationally convenienient and reasonable approximation.

For the consumers who are informed that their current plan will be changed in the future and no longer be available, the decision problem changes. We will allow this event to have a direct impact on attention itself, but it should be expected to change current behavior even when keeping $\lambda$ fixed, since consumers will take into account that they might be inattentive in the future when the terms actually change. This could lead consumers to change their plan when attentive prior to the change in terms, even if they are on the optimal plan considering the current choice set in isolation.

Denote by $\mathcal{D}_{0}$ the choice set prior to the change, $\mathcal{D}_{1}$ the choice set after the change, and $\mathcal{D}_{C}$ the set of plans that will be changed. In the period when the change is implemented, any previous choice $d \in \mathcal{D}_{C}$ will be changed to $\tilde{d}$. Letting $C(d)$ be an indicator for
$d \in \mathcal{D}_{C}$, and assuming that consumers do not expect any further changes to the choice set in the future after the change is implemented, the ex ante value function in the period the change takes place can be written

$$
\begin{equation*}
\bar{V}\left(d, \mathcal{D}_{1}\right)=I_{\mathcal{D}_{1}}+\frac{1-\lambda}{\lambda}[C(d) u(\tilde{d})+(1-C(d)) u(d)] \tag{10}
\end{equation*}
$$

where we have set $\beta=1$. The choice specific value function in the period before the change $\left(t_{c}-1\right)$ is then obtained by inserting into Equation (7):

$$
v_{t_{C}-1}(d)=I_{\mathcal{D}_{1}}+C(d)\left(u(d)+\frac{1-\lambda}{\lambda} u(\tilde{d})\right)+(1-C(d)) \frac{1}{\lambda} u(d)
$$

which for the plans that will be changed next period $(C(d)=1)$ reflects the expected time of being stuck with payoff $u(\tilde{d})$ due to inattention, adjusted for the difference between $u(d)$ and $u(\tilde{d})$ in the same period. To see the intuition behind this expression, imagine a consumer for which $d$ is the optimal plan in $\mathcal{D}_{0}$, while there are better plans than $\tilde{d}$ in $\mathcal{D}_{1}$. Then there is a tradeoff between the gain from getting one last period on the optimal plan against the loss of an expected $\frac{1-\lambda}{\lambda}$ subsequent periods on a disoptimal plan, where this gain and loss is evaluated against the best plan other than $d$ that will be available both before and after the change. ${ }^{19}$ For the plans that will not be changed, the choice specific value is the same as in Equation (9). Choice probabilities are given by the multinomial logit formula with $v_{t_{C}-1}(d)$ for each plan in $\mathcal{D}_{0}$ as arguments.

The ex ante value function for the period before the change (which is the relevant continuation value for the decision two periods before the change), can be found by inserting for (10) in (5), which yields

$$
\begin{gathered}
\bar{V}_{t_{C}-1}\left(d, \mathcal{D}_{0}\right)=\lambda I_{t_{C}-1}+(1-\lambda) I_{\mathcal{D}_{1}} \\
+(1-\lambda)\left[C(d)\left(u(d)+\frac{1-\lambda}{\lambda} u(\tilde{d})\right)+(1-C(d)) \frac{1}{\lambda} u(d)\right] .
\end{gathered}
$$

[^37]Again, inserting this value into Equation (7) yields the choice specific value function two periods before the change

$$
\begin{aligned}
v_{t_{C}-2}(d) & =\lambda I_{t_{C}-1}+(1-\lambda) I_{\mathcal{D}_{1}} \\
& +C(d)\left((2-\lambda) u(d)+\frac{(1-\lambda)^{2}}{\lambda} u(\tilde{d})\right)+(1-C(d)) \frac{1}{\lambda} u(d) .
\end{aligned}
$$

The general form of the choice specific value function with a known change $s$ periods in the future is

$$
\begin{aligned}
v_{t_{C}-s}(d) & =\sum_{\tau=1}^{s-1}(1-\lambda)^{s-1-\tau} \lambda I_{t_{C}-\tau}+(1-\lambda)^{s-1} I_{\mathcal{D}_{1}} \\
& +C(d)\left(\sum_{\tau=0}^{s-1}(1-\lambda)^{\tau} u(d)+\frac{(1-\lambda)^{s}}{\lambda} u(\tilde{d})\right)+(1-C(d)) \frac{1}{\lambda} u(d),
\end{aligned}
$$

though we will only need the values up to two periods in advance, since the relevant customers are notified two months prior to the change.

Note that the inclusive value terms will be irrelevant in the choice probabilities, as they shift all choice values by the same amount given the consumer's available choice set.

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[^0]:    ${ }^{1}$ Literature on status quo and preference biases includes Kahneman and Tversky (1979), Kahneman, Knetsch and Thaler (1991) and Samuelson and Zeckhauser (1988). Additional literature includes Johnson and Goldstein (2003) and Laibson (1997). See e.g. DellaVigna (2009) for a literature summary.
    ${ }^{2}$ Cf. Erikson (1971), Gelman and King (1990), Cox and Katz (1996), and Katz and King (1999).
    ${ }^{3}$ Cf. Thaler and Sunstein (2009) and Handel (2013).

[^1]:    ${ }^{4}$ Seats among ties are determined by lotteries among ties in Hyytinen et al. (2017).

[^2]:    *I am grateful for the comments and suggestions made by Christian Brinch, Jon Fiva, Gorm Grønnevet, Bjørn Hansen, Bjørn-Atle Reme, Christian Riis, Steve Pischke, Jose de Sousa and Frode Steen
    ${ }^{\dagger}$ BI Norwegian Business School and Telenor Research. E-mail: helene-lie.rohr@telenor.com. The author's time is party founded by Telenor Research and partly founded by the Research Council of Norway. The views expressed in this paper are those of the author, and do not necessarily reflect the views of Telenor Research.

[^3]:    ${ }^{1}$ This paragraph focuses on how consumers behave. For survey of the literature on competition and price discrimination in the service industry, see Lambrecht et al. (2012).
    ${ }^{2}$ An aversion to pay overage fees, i.e. the marginal prices above the included allowance in three-part tariffs.

[^4]:    ${ }^{3}$ Prepaid customers and business customers are not included. In addition, I leave out consumers aged 21 and below to increase the probability of customers paying their own expenditures. I also exclude a group of consumers exposed to a price change two months before the event I study, and consumers with plans that have not been sold in the market recently as I lack full overview of these customers' actual prices and discounts.
    ${ }^{4}$ International traffic and roaming are priced more or less the same across all price plans.

[^5]:    ${ }^{5}$ Contrary to the case in Grubb (2015a).
    ${ }^{6}$ Without a data package, the operator reduces speed and caps expenditures at a certain level.
    ${ }^{7}$ About 30 percent of consumers have binding agreements in that they have to compensate the operator for churning (leave the operator) within the contract period. Switching to another price plan within the same operator is normally allowed without compensation, as long as the customer switches to a plan with at least as high a monthly fixed fee.
    ${ }^{8}$ About 5 percent of the customer base have opted to receive e-mails from the operator. Unfortunately, I do not know who these customers are. In addition, customers may have contacted customer service or sales agents directly and gotten information about the launch. I do not know who those consumers are either. The operator uses digital platforms including social media to market their products, implying that consumers can be exposed to personalized marketing.
    ${ }^{9}$ Figure A. 1 in the appendix shows a slight increase in operator's revenues after the launch of the new price plans, indicating that the launch may have been profitable.

[^6]:    ${ }^{10}$ Switching rates are also substantially higher during the first four months of the sample, compared to the months right before new price portfolio became public. The high switching rates during the first four months are a result of a pre-Christmas campaign, giving consumers up to three months of more data if they switched to a few selected price plans.

[^7]:    ${ }^{11}$ Note that potential savings is a measure without any normative implications.

[^8]:    ${ }^{12}$ In the choice between a flat rate and a pay-per-use tariff for fixed telephony.
    ${ }^{13}$ All figures are shown in a monetary unit in which 1 unit is approximately 1 Euro.

[^9]:    ${ }^{14}$ The checkered pattern is due to the price structures, by which make most customers have potential saving in the five multiplier. The similar price structure results in the pattern of the left hand panel of Figure 2.

[^10]:    ${ }^{15}$ There is a literature on how marginal prices affect consumption in similar markets. Nevo, Turner and Williams (2016) analyze the intra-month allocation of fixed Internet data volumes, and find that consumers are forward-looking and responsive to the shadow prices of data consumption. Lambrecht, Seim and Skiera (2007) find that access and usage prices are more likely to influence choice of plan than usage in demand for fixed Internet access under three-part tariffs. Ito (2014) shows that, under non-linear pricing, consumers respond to average price rather than marginal price in their consumption of electricity.

[^11]:    ${ }^{16}$ The pre-period include four typical high volume periods, autumn holidays, Christmas holidays, winter holidays and Easter.
    ${ }^{17}$ The basic results cluster individuals on ex ante price plan choice under common market conditions. Results with alternative clustering of the standard errors are presented in appendix B.

[^12]:    ${ }^{18}$ Point estimates of $\beta$ in Equation 3 are reported in the Appendix, panel A of Figure A.3. There is a striking consistency in the results if I replace consumption in the calculation of change in potential savings with i) individual average of minutes, SMS, and megabytes in the three months period before the portfolio launch, cf. panel B of Figure A.3, and ii) each consumers highest use of minutes, SMS and megabytes throughout the pre-period, cf. panel C of Figure A.3. Overage aversion (Ater and Landsman, 2013) and loss aversion (Genakos, Roumanias and Valletti, 2015) can result in consumers caring more about periods of high consumption, and the pre-period includes four potential high usage periods (autumn vacation, Christmas, winter vacation, and Easter). My results are consistent across the three measures of pre-usage.

[^13]:    ${ }^{19}$ Five Euros was chosen as a splitting point to ensure a high enough number of customers in the group with a rise in their potential to save, cf. Figure 5.
    ${ }^{20}$ Appendix B present results with alternative clustering influencing the standard errors.

[^14]:    ${ }^{21}$ Looking at the company's expenditures on sales, marketing, and commissions, Figure A. 5 in the Appendix, it is not clear how marketing activities drive switching. These expenditures do not correlate closely with the switching rates. Even so, these budgets may have been used differently during the period and therefore had different impact on switching rates. Unfortunately, I am unable to differentiate these expenditures further.

[^15]:    ${ }^{22}$ In the largest city, I use administrative area's median income.
    ${ }^{23}$ Point estimates are illustrated in the Appendix, Figure A.6.
    ${ }^{24}$ Age is likely to be correlated with income, but splitting consumers by age does not change the result.

[^16]:    ${ }^{25} 1,557$ respondents which are customers of the operator.

[^17]:    ${ }^{26}$ Figure 2 shows the histogram of average ex ante potential savings. The first quartile has an average potential save of about 5 Euros or less. The second, about 5-10, the third, about 10-15, and the fourth above 15 .

[^18]:    ${ }^{27}$ Point estimates of the $\beta \mathrm{s}$ from all quartiles are reported in the Appendix in Figure A.7, but no of the other estimates are significantly different from zero.

[^19]:    ${ }^{28}$ The mass marketing campaign aimed at both increase the brand awareness and inform about product and prices.

[^20]:    ${ }^{29}$ According to OECD telecommunication price baskets in 2012 (http://www.oecd.org/sti/broadband/price-baskets.htm), all Nordic market are among the $1 / 3$ least expensive markets.

[^21]:    ${ }^{30}$ The point estimates reported here are not the same as those in the main analysis, as the present analysis were conducted on a random sample of 20 percent of the customers.

[^22]:    Keywords: Consumer Inertia, Inattention, Consumer Behavior, Telecom, Churn.

[^23]:    *We wish to thank Eva Ascarza, Jon Fiva and Andreas Kotsadam for their discussions and invaluable inputs. The paper has also benefited from the comments of seminar participants at the Norwegian School of Economics and the Norwegian Business School.
    ${ }^{\dagger}$ Telenor Research and The Choice Lab. E-mail: Bjorn-Atle.Reme@telenor.com. The author's time is founded by Telenor Research.
    ${ }^{\ddagger}$ BI Norwegian Business School and Telenor Research. E-mail: helene.l.rohr@bi.no. The author’s time is founded by Telenor Research and the Research Council of Norway. The views expressed in this paper are those of the author, and do not necessarily reflect the views of Telenor Research.
    ${ }^{\S}$ Norwegian School of Economics. E-mail: morten.saethre@nhh.no

[^24]:    ${ }^{1}$ Studies of consumer inertia: Madrian and Shea (2001) and Dube et al. (2010). Studies of consumer inattention: Miravete and Palacios-Huerta (2014), Grubb (2015b) and Ho et al. (forthcoming). Other related topics are the literatures on the status quo bias (Samuelson and Zeckhauser, 1988) and salience (see for instance Bordalo et al., 2013).

[^25]:    ${ }^{2}$ We only include customers who carry the cost of their own mobile usage, hence minors (age below 21) and business customers are excluded. After these restrictions, we are left with approximately one million customers in our final dataset.
    ${ }^{3}$ In the first month of our sample, we have about 320,000 customers on plans which would be removed, though this number decreases to 270,000 in the month prior to notification, both due to churn and due to customers changing to other calling plans.
    ${ }^{4}$ One of these plans had already existed in the market for three years, while the other was introduced at the same time as the plan removal. Neither of the price plan had been actively marketed prior to the March 2014.

[^26]:    ${ }^{5}$ Table A. 1 and Table A. 2 in the appendix give an overview of the important prices for the removed plans along with the new, assigned plans.
    ${ }^{6}$ One of the price plans sees an influx of 6,200 new customers from the beginning of our sample to notification, which is small both compared to the total sample, as well as the 100,000 customers who were initially on the same plan. The results we show have this group included in the sample, though our results are unchanged whether we include these customers or remove them from the sample.

[^27]:    ${ }^{7}$ Save $_{i}=\operatorname{average}\left[\operatorname{cost}\left(\right.\right.$ plan $\left.\left.^{i} \mid X_{i}\right)\right]-\operatorname{average}\left[\operatorname{cost}\left(\right.\right.$ plan $\left.\left.^{\text {new }} \mid X_{i}\right)\right]$, where plan ${ }^{i}$ is the actual pre-plan, and $X_{i}$ is actual pre-consumption, both of consumer $i$.
    ${ }^{8}$ Place of residency is categorized using the operator's categorizes.

[^28]:    ${ }^{9}$ More precisely, customers on the reassigned plans. Customers that churn before the poking are not poked.
    ${ }^{10}$ For about half the customers leaving the company we have the exact date they leave. If we plot churn based on only customers with registered churn date, there is no increase in churn among the poked customers before the poking date (cf. Figure A.2). Due to lack of exact churn date for the rest of the customers, churn is registered as the last month a customer use the subscription to call, send SMS or be connected to the Internet. If a customer leaves in March, before using the phone at all in March, churn is registered in February. The poked customers have on average lower traffic volumes than the non-poked customers (cf. Table 1). Hence, they are more likely to not have used their phone at all before the poke, in the month they were poked.

[^29]:    Note: The poked group are customers who hold one of the reassigned plans at time of poking, or customers who left the company while holding one of the reassigned plans, but left before the time of poking. The other are customers on plans which are not reassigned. Pre indicates the six month prior to the poking, while post is the 17 month from the poking month. Standard deviations in parentheses.

[^30]:    ${ }^{11}$ Pre-paid services usually do not have regular payments, and usage is limited by the extent to which the customer has paid in advance for megabytes, sms and voice calls.

[^31]:    ${ }^{12}$ In practice, we estimate the parameters using a triple difference model.
    ${ }^{13}$ We cluster standard errors on which price plan they hold before the poke, and under which market conditions they entered that price plan, i.e. customers entering the same price plan in the same month are in the same cluster. Clustering observations by customer clearly reduces the standard errors.

[^32]:    ${ }^{14}$ The change in the monthly fixed fee is more salient than the other price changes. Hence, we could assume customers who experience a larger increase in the fixed fee to be more prone to churn (cf. Grubb, 2015a; Bordalo et al., 2012; Gabaix and Laibson, 2006). We do not find any difference in the poking effect for customers facing a large increase in the fixed fee compared to a small increase.
    ${ }^{15}$ All customers experience an increase in the fixed fee, cf. Table A. 1 and Table A.2. In the telecom industry, bill shocks - an unusually high bill-are perceived to increase the propensity to churn (c.f. Grubb, 2015b). Even so, in the before period, bill shock does not correlate with churn, and we do not find evidence for a recent bill shock to explain the churn increase in the during period among the poked customers.

[^33]:    ${ }^{16}$ Cf. Table A. 3 versus Table A. 1 and Table A.2.

[^34]:    ${ }^{17}$ Note that this expression is only valid if $p_{i t}^{A}$ (and $v_{i j t}$ ) is fixed over time, or if we assume that the customer expects his current "level of attention" to last into the foreseeable future. Otherwise, the correct expected duration is $\sum_{\tau=1}^{\infty} \tau p_{i t}^{A}\left(1-p_{i t}^{A}\right)^{\tau-1}$. Since the differences in terms of implications for choice behavior in our model should be small, we opt for using the simpler expression for our analysis, also since it would anyway not be clear how we should extend $p_{i t}^{A}$ out of the time-frame of our sample, in addition to what we find an unreasonable assumption of customers having perfect foresight of changes in future inattention.

[^35]:    ${ }^{18}$ See the Appendix, Table A. 5 for a table of coefficients.

[^36]:    Note: The upper part of the table shows estimation results of the coefficients from the estimation in stage 1, while the lower part of the table shows coefficient from estimating the second sage of the model, the choice of provider conditional on being attentive. Current provider refers to the relevant company.

[^37]:    ${ }^{19}$ We have here assumed that the consumer cannot choose a plan that will be changed in the subsequent period other than the one he is currently subscribing to, which was the case in our empirical setting.

