Loss aversion on the phone[1]

Christos Genakos[2], Costas Roumanias[3] and Tommaso Valletti[4]

September 2015

Abstract

We analyze consumer switching between mobile tariff plans using consumer-level panel data. Consumers receive reminders from a specialist price-comparison website about the precise amount they could save by switching to alternative plans. We find that the effect on switching of being informed about potential savings is positive and significant. Controlling for savings, we also find that the effect of incurring overage payments is also significant and six times larger in magnitude. Paying an amount that exceeds the recurrent monthly fee weighs more on the switching decision than being informed that one can save that same amount by switching to a less inclusive plan, implying that avoidance of losses motivates switching more than the realization of equal-sized gains. We interpret this as evidence of loss aversion. We are also able to weigh how considerations of risk versus loss aversion affect mobile tariff plan choices: we find that a uniform attitude towards risk in both losses and gains has no significant influence on predicting consumers' switching, whereas perceiving potential savings as avoidance of losses, rather than as gains, has a strong and positive effect.

Keywords: Loss aversion, consumer switching, tariff plans, risk aversion, mobile telephony

JEL Classification: D03, D12, D81, L96

---

[1] We thank seminar audiences at several universities and conferences for useful comments. We especially thank Stelios Koundouros, founder and CEO of Billmonitor.com, for sharing the data and his industry experience with us. The opinions expressed in this paper and all remaining errors are those of the authors alone.

[2] Athens University of Economics and Business, Centre for Economic Performance & CEPR, E: cgenakos@aueb.gr, U: http://www.aueb.gr/users/cgenakos

[3] Athens University of Economics and Business, E: roumanias@aueb.gr, U: http://www.aueb.gr/users/roumanias

[4] Imperial College London, University of Rome "Tor Vergata" & CEPR, E: t.valletti@imperial.ac.uk, U: http://www3.imperial.ac.uk/people/t.valletti

1. Introduction

Understanding consumer choice behavior under uncertainty is a central issue across a range of social sciences. Following Kahneman and Tversky's (1979) and Tversky and Kahneman's (1992) pioneering work, a large literature has shown that individuals evaluate economic outcomes not only according to an absolute valuation of the outcomes in question, but also relative to subjective reference points. Loss aversion, one of the pillars of prospect theory, asserts that losses relative to a reference point are more painful than equal-sized gains are pleasant. Yet, despite the overwhelming laboratory evidence,[5] relatively few field studies document this phenomenon, and the ones that do involve choices in which risk plays a minor, even non-existent, role.

In this paper, we present novel evidence that loss aversion plays a pivotal role in explaining how people select their contracts in the mobile telecommunications industry. We use a new individual-level panel dataset of approximately 60,000 mobile phone users in the UK between 2010 and 2012. Consumers in our sample subscribe to monthly plans with a fixed payment component (the monthly rental) that includes several allowances (for call minutes, text messages, data usage, etc.). We argue that the monthly rental payment provides a natural reference point. If a customer exceeds her allowance, she pays extras fees, called overage fees. This customer could save money by switching to a higher, more inclusive, plan. A customer could also save money by switching to a lower, less inclusive tariff if her consumption is systematically lower than her allowance. We conjecture that, in line with loss aversion, paying more than the reference point is a more "painful" experience and should prompt consumers to switch with higher probability than they would if they could save the exact same amount by switching to a lower tariff.[6]

A unique feature of our data is the way that savings are calculated. In general, people can make mistakes in predicting their phone usage or have a limited ability to compute the savings from the many available alternatives, which might generate both biases and inertia. In our setting, phone users have registered with a specialist mobile comparison website, and customers' potential savings are calculated by an optimizing algorithm devised by a company that is allowed to look into their past bills. Consumers then receive personalized information

[5] For an excellent summary of this evidence, see Camerer et al. (2004).

[6] Kahneman (2003), in his Nobel acceptance speech, similarly observed: "The familiar observation that out-of-pocket losses are valued much more than opportunity costs is readily explained, if these outcomes are evaluated on different limbs of the value function."

on the exact amount they could save by switching to the best contract for them. In other words, it can be argued that in our sample, consumers *know* precisely how much they can save by switching to a lower- or a higher-tariff plan.

Based on this information, we evaluate the within-person changes affecting the likelihood of switching contracts over time. We show that potential savings are a significant determinant of switching. More importantly, and in line with our loss-aversion conjecture, we find that, controlling for savings, switching is six times more likely if the customer was charged overage fees.

The case of the mobile phone industry is of particular interest, as mobile phones are ubiquitous and people spend a considerable amount of money on them.[7] Our findings are also applicable beyond cellular services to many economic settings in which consumers choose "three-part" tariff contracts that specify fixed fees, allowances, and payments for exceeding the allowances (e.g., car leases, credit cards, subscription services; see Grubb, forthcoming). Note that these environments are, almost by definition, uncertain, as there is a random element in people's behavior that determines what is ultimately consumed and charged. This uncertainty brings with it an element of risk.

Placing risk aversion vis-à-vis loss aversion is of economic importance, as, in many real-life environments, the potential of both gain and loss is most likely to co-exist with risk. In situations of choice under uncertainty, prospect theory first foregrounded the importance of loss versus gain, whereas expected utility theory typically assumes a uniform attitude towards risk. Although a large body of literature has focused on assessing the relevant merits of the two theories (e.g., Rabin, 2000; Fehr and Göette, 2007), to the best of our knowledge, no one has attempted to account for both with field data. We believe that this is important, as we do not see loss aversion and risk aversion as antagonistic, just as we do not necessarily see loss aversion and traditional expected utility theory as mutually exclusive. In principle, they can both help us understand the determinants of choice. Given the appropriate data, it becomes an empirical question to test whether the predictions from either theory are consistent with the data, as well as the extent to which they can help predict observed behavior. In this study, we do not assume or impose constraints on our consumers but, rather, allow both risk and loss aversion to affect their choices.

[7] In the UK, mobile revenues have been stable at over £15bn ($23bn) per year over the past decade. This corresponds to about £200 ($300) per year per active subscriber. See Ofcom (2013).

Testing for the influence of both, we actually find that risk aversion cannot explain consumers' switching, as traditional expected utility theory would suggest, whereas loss aversion remains strong and significant under all specifications examined. We also find that individuals seem to be risk-averse in the domain of gains and risk seekers in the domain of losses: this differential risk attitude, resulting in an S-shaped behavior of their value function, is consistent with prospect theory.[8]

Our work is related to a large empirical literature on consumer search and choice behavior. Five key aspects distinguish our work from earlier studies.[9] First, we use actual consumer-level information from a large sample of consumers in an advanced economy.[10]

Second, the leading mobile price comparison site in the UK calculates the savings, and each consumer receives personalized information via email. Thus, in our environment, customers should suffer significantly less from "comparison frictions," as in Kling et al. (2012), who show that simply making information available does not ensure that consumers will use it.

Third, we test for loss aversion in an environment in which uncertainty is not fixed. Existing work typically establishes an asymmetric attitude between gains and losses either when choices are riskless (the example of the "endowment effect")[11] or in environments in which uncertainty is excluded as an explanation of observed behavior because it is held constant throughout the experiment. For example, Fryer et al. (2012) present evidence of loss aversion by fixing the mean and variance and exposing subjects to choices between losses and gains in a field experiment in education. Teachers were shown to have better results when faced with a compensation program that initially presented them with a bonus that was taken away if targets were not met (loss) than when facing the same average compensation and same

[8] Genesove and Mayer (2001) observe that house market prices are more flexible upward than downward, which implies that sellers' reservation prices are less flexible downward than buyers' offers. They suggest that the sellers' reservation price depends on the purchase price of their house (reference point). Sellers with an expected selling price below the purchase price set a reservation price that is higher than the price set by sellers who do not incur losses. This is also what we find in our data.

[9] There is a large body of literature summarizing the main theories of individual decision making in psychology and economics. Rabin (1998), DellaVigna (2009), Barberis (2013), Kőszegi (2014) and Chetty (2015) provide excellent reviews of the evidence in the field.

[10] In related work, Jiang (2012) uses survey data from the US, whereas Grubb (2009) and Grubb and Osborne (2015) use data from a student population only.

[11] The "endowment effect" is the observation that experimental subjects, who are randomly endowed with a commodity, ask for a selling price that substantially exceeds the buying price of subjects who merely have the possibility to buy the commodity (see, e.g., Kahneman et al., 1990; Knetsch, 1989). List (2003, 2004) questions the robustness of this effect, demonstrating that experienced dealers are much more willing to exchange an initial object they are given for another one of similar value. However, Kőszegi and Rabin (2006) argue that List's results may be fully consistent with prospect theory, and more recent research tries to explore this hypothesis further (Ericson and Fuster, 2011; Heffetz and List, 2014).

variance that awarded them a bonus only if targets were met (gain). Similarly, Pope and Schweitzer (2011) show that professional golfers react differently to the same shot when they are under par than when they are over. Although this clearly provides evidence of asymmetric reaction to loss, golfers over par do not face a more uncertain environment than those under par, so loss aversion cannot be tested alongside risk aversion. Our environment offers a natural interpretation of loss-gain asymmetry, and, furthermore, variance can be easily and naturally measured through bill variability to provide an index for testing risk's contribution to consumer choice. In other works, authors have taken stances in favor of one or the other, while arguing that alternative explanations would not be realistic in the setting they study. For example, Cohen and Einav (2007) estimate risk aversion in insurance and argue that alternative preference-based explanations are not relevant in their context, while Ater and Landsman (2013) study retail banking and base their approach on loss aversion, reasoning that risk plays a minor, possibly non-existent, role.

Fourth, we analyze a context in which switching can ensure rather large monetary savings. In related research, Ater and Landsman (2013) analyze customers' switching decisions after observing the overcharges on their previously held plans in a retail bank. They find that customers who incur higher surcharges (losses) have a greater tendency to switch, a finding that we also share. However, despite the large estimated effect of surcharges, the absolute monetary value in their case is very small compared to average consumers' income or savings. Moreover, their data do not allow them to distinguish between classic risk aversion and loss aversion: it is possible that customers with risk aversion choose systematically higher plans than needed and switch more rarely. Most importantly, although Ater and Landsman (2013) calculate potential savings *ex post*, it is not likely that customers themselves know or could easily calculate the level of savings *before* their switching decision. So it is possible that customers with overage react to what they perceive as a savings opportunity, which customers with usage that falls below their allowance cannot easily detect or calculate. In this, our framework is drastically different. Our customers are *explicitly* informed about their potential savings by an expert company that they have chosen to register with. So they are fully aware of their potential savings when they make their switching decisions. Asymmetries cannot be attributed to misconstruing overage as a greater savings opportunity.

Fifth, we study telecoms in a mature phase of the industry. We expect customers in our sample to have considerable experience in searching and selecting among operators' tariffs, given that mobile penetration has exceeded 100% of the population since 2004 in the UK,[12] and that mobile operators have tried and tested their pricing schemes to optimize profits in a highly competitive industry.[13]

In this paper, we concentrate on understanding the determinants of consumer switching. We do not attempt to evaluate the optimality of consumers' decisions and refrain from making welfare claims.[14] Therefore, though closely related, our application of behavioral economics to cellular phones is different from the extant literature on overconfidence and flat-rate bias.[15]

The remainder of the paper is organized as follows. Section 2 introduces the UK mobile communications industry and describes the consumer-switching problem. Data are presented in Section 3, while Section 4 introduces the empirical strategy. Results are discussed in Section 5, alongside several robustness checks. Section 6 concludes.

2. The industry and the consumer decision process

2.1 Mobile communications in the UK

Mobile communications in the UK are provided by four licensed operators: Vodafone, O2 (owned by Telefonica), Everything Everywhere[16] and the latest entrant, Three (owned by Hutchison). They all provide their services nationally. In 2011 (midway through our sample), there were 82 million mobile subscribers among a population of 63 million. These subscribers were split 50:50 between pre-paid (pay-as-you-go) and post-paid (contract) customers. The latter typically consume and spend more than the former.

---

[12] Hence, we differ, e.g., from Miravete (2002), who considers the early days of the US cellular industry, and from Jiang (2012), who also uses early data to simulate policies introduced later.

[13] Our paper is also related to recent literature that has exploited rich data from cellular companies to analyze a wide range of issues, such as optimal contracts (Miravete, 2002), consumer inertia (Miravete and Palacios-Huerta, 2014), as well as competitive dynamics and the impact of regulation (Economides et al., 2008; Seim and Viard, 2011; Genakos and Valletti, 2011).

[14] We have no information on the tariff recommended by the comparison website, and, hence, we cannot evaluate whether customers followed that advice or chose some other tariff.

[15] Using cellular contracts, Lambrecht and Skiera (2006), Lambrecht et al. (2007) and Grubb and Osborne (2015) discuss how, in the presence of mistakes related primarily to underusage, the consumers' bias might be systematic overestimation of demand and could cause a flat-rate bias. Were mistakes due primarily to overusage, the consumers' bias might be systematic underestimation of demand, consistent, instead, with naive quasi-hyperbolic discounting (DellaVigna and Malmendier, 2004).

[16] Everything Everywhere was formed after the 2009 merger between Orange and T-Mobile (owned by Deutsche Telekom).

The industry is supervised by a regulator, the Office of Communications (Ofcom). The regulator controls licensing (spectrum auctions) and a few technical aspects (such as mobile termination rates and mobile number portability), but, otherwise, the industry is deregulated. Operators freely set prices to consumers. The four operators have entered into private agreements with Mobile Virtual Network Operators (MVNOs) to allow them use of their infrastructure and re-branding of services (e.g., Tesco Mobile and Virgin Mobile). These MVNOs typically attract pre-paid customers and account for less than 10% of the overall subscriber numbers (and less in terms of revenues).

Post-paid tariff plans are multi-dimensional. They include a monthly rental, a minimum contract length, voice and data allowances, and various add-ons and may be bundled with a handset and various services. Pre-paid tariffs have a simpler structure.

As in other industries, there have been concerns about the complexity of the tariffs and the ability of consumers to make informed choices. Ofcom, however, has never intervened directly in any price setting or restricted the types of tariffs that could be offered.[17] Instead, Ofcom has supported the idea that information should let consumers make better choices, as consumers are more likely to shop around when there is information available with which to calculate savings from switching tariff plans. The regulator has, therefore, awarded accreditations to websites that allow consumers to compare phone companies to find the lowest tariffs. In 2009, Billmonitor.com (henceforth BM), the leading mobile phone price comparison site in the UK, was the first company to receive such an award for mobile phone services, and its logo appears on Ofcom's website.[18]

Based on Ofcom's (2013) report, the annual switching between operators (churn rate) varies between 12% and 14% for the years 2010-2012. There is no publicly available data on within-operator switching, as this is private information held by operators. In the BM sample, we observe that some 23% of the customers switch contracts within-operator at least once annually during the same period. Although the BM sample consists only of post-paid customers that, on average, consume and spend more, we will demonstrate that it has a very good geographic spread across the UK and closely matches mobile operators' market shares

[17] In the UK, this has instead occurred in the energy and banking sectors. For price controls in the UK energy sector, see https://www.ofgem.gov.uk/ofgempublications/64003/pricecontrolexplainedmarch13web.pdf. For price controls in the banking sector, see Booth and Davies (2015).

[18] http://consumers.ofcom.org.uk/tv-radio/price-comparison/. It is important to note that Ofcom emphasizes the independence of these websites. In the BM case, there is no conflict of interest between the advice that they provide and the choice that consumers make, as the site neither sponsors nor accepts advertising from any mobile provider.

and consumer tariff categories, indicating that it is representative of contract customers rather than prepaid phone customers. Even with this caveat in mind, the high within-operator switching suggests that this is an important and heretofore underappreciated source of switching that can be very informative for understanding consumer behavior.

2.2 The consumer decision process

Upon users' registration with the website, BM attains access to their online bills. BM downloads past bills, calculates potential savings for the user,[19] and then informs the consumer of these potential savings. The process is repeated monthly, as shown in Figure 1. On a typical month t, the bill is obtained on day s of the month. BM logs on to the user's mobile operator account and updates the user's bill history. It uses the updated history to calculate potential savings, which it then emails and texts to the user. Thus, on day s, the consumer receives her bill, followed by an email and a text from BM with potential savings based on her usage history and the current market contract availability. BM also recommends a new plan to the customer. The consumer decides whether to act on the information (switch = 1, don't switch = 0), with no obligation to choose the recommended plan. The decision is reflected in next month's (t + 1) bill. On day s of month t + 1, the consumer receives her new bill. Then, the savings for month t + 1 are calculated and communicated to the consumer, who then decides whether to stay with her current plan, and so on. Thus, the switch decision, eventually observed at time t + 1, is based upon usage and savings information collected and sent to the user at t.

[Figure 1]

BM allows registration only to residential customers with monthly contracts, who are typically the high spenders with more complex tariffs. Two features are immediately relevant for our purposes. First, despite their complexity, all tariffs are advertised as a monthly payment, with various allowances. The monthly payment becomes a relevant reference point for the consumer. We call this anticipated and recurrent monthly payment R, though the

[19] In order to calculate savings and suitable contracts, BM builds possible future call, text and data usage scenarios for each customer, based on past usage. Using an advanced billing engine, cost is calculated for different possible usages for all available market plans. The plan that minimizes the customer's expected cost is chosen, controlling for the variance of bills. The cost for the chosen plan is then contrasted with the cost under the consumer's current plan to obtain savings. All savings recommendations are made with respect to the users' stated preferences at the time they register (e.g., operator, contract length, handset). To protect the intellectual property of BM, the full details cannot be disclosed.

customer may end up paying more than this amount if she exceeds her allowances or uses add-ons not included in the package. In this case, the actual bill, which we denote by B, is greater than R. Second, BM calculates the cost of alternative contracts and, given the expected consumer behavior, picks the cheapest contract for the particular consumer and informs her about it. If C is the cost of the cheapest contract, as calculated by BM, the message that BM sends the user should be informative in at least two respects. First, the customer is directly told the total value of the savings she can make – that is, Savings = $B - C$. Second, the customer is prompted to see if there have been fees for extras not included in in the monthly bundle and if she has exceeded the allowances. This is called "overage" in the cellular industry and happens when $B > R$.

In Appendix A, we present snapshots of some key moments of the customer experience with BM.

3. Data description and summary statistics

For our analysis, we combined four different datasets obtained from BM[20] into a single one with more than 245,000 observations that contain monthly information on 59,772 customers from July 2010 until September 2012. For each customer-month, we have information on the current tariff plan (voice, text, data allowance and consumption, plus the tariff cost), the total bill paid and the calculated savings. [21]

Given that the data come from a price comparison website on which consumers freely register, it is important to examine the representativeness of our sample (see Appendix B for details). [22] We compare observable characteristics of the BM sample with available information on UK mobile users. As noted earlier, BM allows only monthly-paying customers to register, so we do not have information on pay-as-you-go mobile customers.

[20] The four datasets are: the accounts dataset, which contains an anonymized account identification code for each customer who registers with BM, together with her codified phone number and current operator; the bills' dataset, which contains information on the tariff cost, total cost and characteristics of the plan in each month (for example, voice, texts and data allowance); the usage dataset, which contains itemized information of every bill in each month; and the savings dataset, which provides details on the information sent by BM on how much the customer could save by switching to the best available tariff for her.

[21] We do not have information on the suggested tariff plan, which is, however, observed by the user.

[22] All contracts are single-customer contracts, and we do not observe business contracts – i.e., a single entity owning multiple phone contracts.

First, looking at the geographic dispersion, the distribution of our customers closely matches that of the UK population in general (Appendix Figure B1).

Second, the operators' market shares also match quite accurately. The only exceptions are Everything Everywhere, which is slightly overrepresented in our sample, and Three (the latest entrant), where we have a smaller market share in our data compared to data available from the regulator (Appendix Figure B3).

Third, in terms of average revenue per user (ARPU), we have overall higher revenues, which, of course, can be explained by the fact that we have only post-paid customers. Otherwise, the ranking of the operators is roughly equivalent (Appendix Figure B5).

Fourth, we have a good representation of customers in different tariff plans. We can compare our sample with the aggregate information available from Ofcom on the percentage of customers in each segment. The only category that is underrepresented in our sample is the lowest tariff plan, which is, perhaps, reasonable given that there is reason to believe that customers who register with BM are those on larger tariff plans, as they can make bigger savings (Appendix Figure B6).

Finally, according to Ofcom information, customers in our data send 50 more text messages[23] and talk slightly more[24] than the average consumer, which also explains the higher ARPU.

Overall, it seems that our sample has a very good geographic coverage of the UK and is in line with the aggregate market picture of operators and tariffs. The customers in our data seem to be heavier users, but the overall picture is representative of the post-paid (contract) segment in the UK.[25]

3.1 Sample summary statistics

In this section, we highlight some of the most interesting aspects of consumers' behavior in our sample, related to savings, overage and switching.

[23] Based on Ofcom (2013), the average number of SMS per month was 201, whereas in the BM dataset, customers sent 251.
[24] Based on Ofcom (2013), the average minutes per month were 207, whereas they were 235 in the BM dataset.
[25] We do not have information concerning the age or mobile experience of customers. When we control for the number of months that we observe each customer in our data, a proxy for contract tenure, the coefficient is not significant, indicating that, at least within our sample, "experience" does not make any difference for savings.

Savings

A unique aspect of our data is the savings information calculated by BM. A customer can save money (positive savings) by switching to either a lower or a higher tariff plan, depending on her consumption. However, a customer might also have negative savings – that is, the customer would pay more under the best alternative contract than under her current contract: no better deal is available. Figure 2 plots the distribution of monthly savings. The majority of customers have positive savings (73%), with the average being £14 and the median being £11.

[Figure 2]

When conditioning savings on some observable characteristics, we find that female customers have no different savings than men. Likewise, customers throughout the various UK geographic regions have similar levels of potential savings, reflecting the fact that all operators are present nationwide (Appendix Figure B2). Additionally, customers across all operators can save, with some small significant differences among them (Appendix Figure B4).

An interesting phenomenon is the fact that savings increase significantly as one moves to higher tariff plans, ranked in different brackets by monthly rentals, following the definition of Ofcom (Appendix Figure B7).

Overage

Overage is very common: 64% of the customer-months in the BM sample experienced it. If one looks at the actual difference between the bill and the recurrent tariff cost ($B - R$), then the average amount of overspending is £15, with the median being £7. These figures are large when compared to the average monthly bill, which is £25 in our sample. Overage is common across genders, different UK regions, and mobile operators. Also interesting is that overage does not exhibit any particular relationship with different tariff plans and even customers with negative savings experience it (55% of observations with negative savings have overage). Overage is very common, not only because it is caused by consuming over and above one's current tariff allowance, but also because mobile operators charge their customers extra for all sorts of other calls and services, such as helplines, premium numbers, etc.

Switching

For data availability reasons, we examine switching only across different tariff plans offered by the same operator. This is important for two reasons. First, it is relatively easier to switch within-operator compared to switching across operators. Customers can change tariffs with the same provider without paying penalties if they switch prior to the expiry of the contract. Thus, we can be less worried about contractual clauses that we do not observe. Second, within-operator switching is an important source of switching in the mobile industry – as reported earlier, in our data, 23% of customers switch within-operator annually. Hence, this setting is ideal for unraveling frequent consumer choices, though the limitation is that we cannot say much about industry-wide competitive effects.

The average in-sample probability of switching is 0.080 per month, with women switching more often than men (0.083 vs 0.077, p-value = 0.0002). Switching is equally distributed across the UK.

Looking at the savings distribution (Figure 3), switchers (before switching) have higher savings than non-switchers (£9.3 vs £7.3, p-value = 0.000), and their distribution also has a fatter right tail. So savings seem to be one of the factors triggering the decision to switch.

[Figure 3]

Finally, it is worth noting that consumers who had overage on their last bill are also more likely to switch (0.083 vs. 0.075, p-value = 0.000), indicating that overage might also play a role in switching behavior. Table 1 reports some key sample summary statistics.[26]

[Table 1]

4. Empirical framework

To analyze consumer switching behavior, we use the following econometric framework:

$$pr\ (switching)_{it} = \beta_0 + \beta_1 \mathrm{Overage}_{i(t-1)} + \beta_2 \mathrm{Savings}_{i(t-1)} + \mathrm{d}_i + \mathrm{d}_t + \varepsilon_{it}. \qquad (1)$$

[26] Due to the use of lagged values in our estimation framework, we lose the first observation of each consumer, as well as a number of consumers who register for only one month.

The switching probability for individual i at month t depends on two critical pieces of information retrieved at time $t-1$ from BM: *Overage* is a binary variable indicating whether the total bill was higher than the tariff reference cost in a given month (Overage = $1(B, R)$, where $1(\cdot)$ is an indicator function taking the value of 1 if $B > R$, and zero otherwise); and *Savings* is the monthly savings calculated by BM and communicated to the customer. Notice that we correct for unobserved heterogeneity by extensively controlling for fixed effects: d_i captures customer fixed effects, while d_t represents time (joint month-year) fixed effects. Thus, we control for unobserved differences across customers and unobserved time trends and shocks. Finally, ε_{it} is the error term that captures all unobserved determinants of the switching behavior. Our main interest is in the parameter β_1 that describes the impact of overspending last month on the probability of switching now, controlling for the amount that could be saved.

We estimate (1) using mainly a linear probability specification and calculate the standard errors based on a generalized White-like formula, allowing for individual-level clustered heteroskedasticity and autocorrelation (Bertrand et al., 2004). We also estimate a simple and a conditional (fixed effects) logit model. Although such a model is better suited to the binary dependent variable, it is not ideal for our purposes, as the more appropriate FE logit model can be estimated only on a subsample of individuals with variation in the switching variable – i.e., those who switch at least once during the period in which we observe them. This is a nonrepresentative sample and would overestimate the true marginal effect of the independent variables. We provide these results to show the qualitative robustness of our results.

In addition, we also use a proportional hazard model (PHM) for the duration between the time a consumer registers with BM and the time of tariff switching. We estimate (1) utilizing a semiparametric estimation procedure that allows for time-varying independent variables (Cox, 1972). According to the Cox PHM, the hazard function is decomposed into two multiplicative components: $h_i(t, X_i) = h_0(t) \times \lambda_i$, where $\lambda_i \equiv \exp(\beta' X_i)$. The $h_0(t)$ is the baseline hazard function that models the dynamics of the probability of switching (hazard rate) over time; X_i is a vector of individual characteristics, and β is a vector of regression coefficients that includes the intercept; λ_i scales the baseline hazard proportionally to reflect the effect of the covariates based on the underlying heterogeneity of consumers. The main advantage of the PHM is that it accounts for censoring[27] and is flexible enough to allow for both time-invariant (e.g., mobile operator) and time-varying control variables (e.g., savings).

5. Results

The main regression results are reported in Tables 2 and 3. Starting with Table 2, when considered individually, both overage and savings are important in determining a switching decision (columns 1 and 3, respectively). This result is robust to controlling for time and individual fixed effects (columns 2 and 4, respectively), and the coefficients actually increase, indicating that unobserved individual or common factors are biasing the initial estimates downward.

Column 5 reports the results of the full specification when both overage and savings are included in the regression. Although we control for savings, overage still has a large and statistically significant coefficient. Interestingly enough, both variables retain their previously estimated magnitudes, indicating that the processes of savings and overage are orthogonal to each other. More importantly, the economic impact of overage is stronger than that of savings. A £10 monthly savings increases the expected probability of switching by only 0.23%, whereas if a customer's monthly bill is higher than her tariff, the probability of switching increases almost sixfold, to 1.32%.

Results are qualitatively unchanged when we use a logit model given the binary nature of the dependent variable. Column 6 reports the estimated coefficients and column 7 the odds ratios. Both estimated coefficients are positive and significant, but a one-pound increase in savings increases the odds of switching by 0.6%, whereas overage increases the odds by 7.8%.[28]

Finally, the last two columns present the estimated coefficient of the switching hazard model. Again, we find that both overage and savings significantly increase the probability of switching (column 8), where an additional pound of savings increases the hazard of switching by 0.3%, whereas overage increases the hazard of switching by 9% (column 9).

[27] Both right censoring since our sample stops at September 2012 and left censoring since consumers join BM at different points in time.

[28] Results using a conditional (individual fixed effects) logit model are even stronger: a one-pound increase in savings increases the odds of switching by 0.8%, whereas overage increases the odds by 18.3%. If we control for individual fixed effects, the logit approach takes into consideration only the customers who experience switching, so it restricts the sample in such a way that it is not comparable with the other regressions. For this reason, Table 2, column 6 reports the results without individual consumer fixed-effects.

Hence, results from all different estimation models lead to interesting insights regarding customer switching among plans. Our findings suggest that, if a consumer is reminded that her plan is suboptimal – that is, if she could save by switching to another tariff – then the higher the savings, the more likely it is that the customer will switch.[29] This is not particularly controversial and follows from basic economic reasoning. More intriguing, though, is that whether a customer has experienced overage payments, over and above savings, also matters considerably. These customers are also more likely to switch to new tariff plans.

Our results are, therefore, potentially supportive of loss aversion or, more generally, about mental accounting theories, which occur when individuals group expenditures into mental accounts and do not treat money as fungible across categories. In our setting, customers treat fixed monthly payments and overage payments as separate mental accounts, which are associated with different levels of utility. Customers construct reference points based on such monthly fees and distinguish between within-budget savings and overage losses. We find that customers prefer avoiding losses to obtaining gains – indeed, the central prediction of the theory of loss aversion.

[Table 2]

Apart from confirming an asymmetric attitude towards gains and losses, the data also allow us to test two other key aspects of the way consumers choose. First, we test how loss aversion fares when considered together with risk aversion in explaining consumer behavior. We do so because the variability in a consumer's bill is readily calculable, so including variability as an explanatory variable tests its contribution to her choice. Second, we test whether there is an asymmetric attitude towards risk in the domain of gains versus the domain of losses, another key feature of prospect theory.

To test the extent to which risk aversion might be a factor driving the observed behavior of mobile telephony customers, we introduce a measure of the variability of payments that is a good proxy for the importance of fluctuations in payments. More specifically, we construct a new variable, *Bill Variance*, which is the variance of the last three bills of a given customer.[30] This variable then becomes an additional control in our main equation. Table 3 reports the

[29] Consumers switch to both higher and lower tariffs. Of those switching, approximately 55% switch to a lower tariff plan, whereas 45% switch to a higher tariff plan.

[30] Denote the monthly bill as B_{it}. Then, we calculate the average of the last three months, $MA = (B_{it-3} + B_{it-2} + B_{it-1})/3$, and, hence, the Bill Variance is equal to $Var_{it} = [(B_{it-3} - MA)^2 + (B_{it-2} - MA)^2 + (B_{it-1} - MA)^2]/3$.

results:[31] column 1 estimates a simple OLS regression to test the effect of variance on switching. The coefficient of variance is not statistically significant. Column 2 repeats the exercise, controlling for consumer and year-month fixed effects. Variance is now negatively associated with switching, implying that consumers exhibit an appetite for variance (they tend to change contracts with higher variability more rarely).[32] Column 3 examines the effect of overage and savings on switching for the same customer-months. The results obtained in Table 2 remain unchanged.

Having separately examined the effect of overage and variance on switching, we now include both in column 4. The effects of overage and savings remain unaffected; they are still highly significant and positive. The effect of variance, however, is no longer significant, implying that variance cannot account for the observed customer switching. Bill variance is not statistically significant, and does not change previous results in any significant way. While, in principle, both loss aversion and risk aversion could play a joint role in a switching decision, we do not find a role for risk aversion, just for overage payments.

Interestingly, although bill variance is not statistically significant, its interaction with overage is (column 5). Customers with overage switch significantly *less* as their bill variance increases. Hence, consumers in our sample exhibit a risk-loving attitude in the domain of losses (remember that, for overage customers, the bill exceeds their contract tariff and is experienced as loss relative to the reference point). On the contrary, customers with no overage are risk-averse, as they switch more often as variance increases. This is in line with the familiar S-shaped value function from prospect theory, whereby individuals are risk-averse in the domain of gains and risk-loving in losses.

[Table 3]

5.1 Alternative interpretations and robustness

In this section, we test the robustness of our results in relation to alternative interpretations of our findings and to measurement and econometric modeling issues.

[31] Due to the lagged three-month moving average calculation, we lose some 74,192 customer-month observations.

[32] As we explain later, consumers exhibit risk aversion in the domain of gains but an appetite for risk in the domain of losses. When considering how risk affects switching uniformly (that is, in both domains), the latter effect seems to dominate.

1. *Sample selection due to risk aversion*. Loss aversion coexists with uncertainty in our environment. Overage payments can be seen as unexpected payments that customers try to avoid. Although we find that bill variance does not affect the probability of switching, in such an uncertain environment, the degree of risk aversion may still be a factor that could drive the results in a different way: risk-averse customers may select over-inclusive plans to avoid fluctuations in their payments. If the information about overage is related to such fluctuations, these customers then may also be more likely to switch, other things equal.

To investigate this, we divide the sample among small (0 <savings ≤ 3), medium (3 < savings ≤ 11), and large savings (11 < savings ≤ 35).[33] Customers that fall in the small savings bracket are actually very good at predicting their behavior and do not select large buffers (otherwise, BM would also find large savings for them). Those who have large savings may, instead, choose large buffers because of aversion to risk. Yet, as columns 1, 2 and 3 of Table 4 indicate, overage is always significant for all these customers, even though they may differ in several other ways. Results in column 1 are particularly telling: customers with very small savings do not react to the information that they have some small potential savings. Nevertheless, once they are informed about overage, even these customers switch contracts with a higher probability.[34] Comparing columns 1, 2 and 3, we note that the magnitude of overage decreases as savings increase. At the same time, the coefficient of savings is not significant for those who have small potential savings (indicating that these customers are, indeed, making cost-efficient choices); however, it is positive and very significant for the medium bracket and positive and significant, but smaller in size, for the large savings bracket.[35] Hence, as savings increase, loss aversion continues to play a significant, role but the magnitude of its effect is smaller than that of savings.

2. *Overage intensity*. Next, we look again at the magnitude of overage. Specifically, we consider the actual amount by which a bill is higher than the monthly reference tariff, and we split the overage observations above and below the median. Table 4, column 4 shows that the higher the overage, the more likely it is that the consumer will switch, while still controlling

[33] Cut-off points correspond to the 10th and 90th percentiles of the savings distribution. Results are robust to alternative cut-off specifications.

[34] For customers with small savings, consumption matches their chosen plans closely. Small consumption shocks (positive or negative) can push them either above or below their allowances, so overage in this case can be thought of as quasi-randomly allocated across these consumers. Results are very similar if we use a symmetric savings range of -3 < savings ≤ 3.

[35] The coefficient on savings increases in magnitude, compared to the main results in Table 2 for the overall sample since we now condition on positive savings.

for the magnitude of savings. This seems to indicate that it is not just overage, but also its magnitude, that play an important role in pushing consumers to switch. The higher the "shock" associated with overage, the more likely consumers will be to switch to a different tariff.

3. *Contract constraints*. Recall that, when consumers register in BM, they are asked to express their preferences related to the operator that they want BM to search, as well as the features they are interested in (e.g., a special handset). If a consumer does not select anything, then BM looks at the universe of available tariffs. Switching between operators can be more difficult than switching within an operator, as there may be additional costs involved. In Table 4, column 5, we select consumers who explicitly include their current operator in their search. As one can see from the number of observations, the vast majority include their current operator, so savings must be informative. The results clearly do not change. In column 6, we adopt a more conservative approach and restrict the analysis to those customers who select *only* their current operator. In this case, savings must indicate that the best alternative contract is with their operator and, hence, must be much more informative. Even with this restriction, the results still hold.

4. *Placebo test: negative savings*. As a placebo test, we also examine the behavior of consumers with negative savings. These customers currently have plans with very good tariffs since BM cannot find cheaper alternatives. However, even these consumers can experience an overage (55% of the observations of customers with negative savings have experienced overage), as a total bill is very often the consequence of various extra charges unrelated to the tariff bundle. But these customers, precisely because their savings are negative, should not be triggered to take a closer look at their bills, and, as a result, they do not notice overage. Hence, we would not expect these customers to react either to their savings or to their overage information. In Table 4, column 7, we find that both coefficients are not statistically significant.

5. *Differences in reactions*. Another possible interpretation of our findings is that consumers who over-consume behave differently than those who under-consume. In particular, one could argue that consumers who over-consume and experience overage can respond only by adjusting their tariff, whereas consumers who under-consume can adjust either their consumption or their tariff. Hence, probabilistically, consumers with no overage are less likely to switch. We find this explanation unappealing for three reasons. First, there is no

clear a priori reason why consumer who under-consume can adjust their consumption more easily than consumers who over-consume. In principle, both can alter their calling behavior when they receive the relevant information from BM. Second, for those consumers in the small savings bracket that we analyzed earlier (Table 4, column 1), the differences between under- and over-consumers are very small, yet overage continues to play a significant role. Third, the argument above would imply that since most of the switchers are over-consumers, the direction of the switching should be for people to increase their tariffs. However, what we observe is that 58% of the consumers who switch choose a lower tariff, while the remaining 42% switch up, which, again, cannot be reconciled with the above argument. This holds true also for consumers in the small savings bracket, (50% switch up and 50% switch down), showing once again that risk aversion alone cannot explain switching behavior.

6. *Learning*. Finally, a variant of the above argument is that consumers learn about their optimal bundle by starting with a low tariff plan that they subsequently increase. Thus, the positive coefficient on overage actually captures the consumer's learning process and not loss aversion. We also find this explanation unconvincing in explaining switching. First, we study UK consumers' behavior in a mature phase of the telecoms industry. Hence, although we do not have information on their age, it is highly unlikely that all these customers are first-time users, unaware of their needs and consumption pattern. Second, if the learning hypothesis were true, then we would expect the direction of switching to be, on average, upwards, and this increase to be more evident the lower the tariff category. However, as we argued earlier, consumers switch to lower tariffs, on average (58% vs 42%), and this tendency actually increases as we move to lower tariff categories (see Figure A1 in the Appendix).

[Table 4]

Next, we consider alternative econometric specifications and also experiment with alternative measures for some of the key variables. First, controlling for Bill Variance does not alter any of the previous results, irrespective of the estimation method or sample selected. In Table 3, column 4, we showed that the coefficient on Bill Variance was not statistically significant and did not affect the size and statistical significance of overage or savings. This continues to be the case, even if we apply the logit model or the Cox PHM as alternative estimation methods (Table A1, columns 1-4). Moreover, controlling for Bill Variance does not alter the results on the saving brackets of Table 4, columns 1-3. Using the same framework, but now controlling for Bill Variance, provides qualitatively very similar results (Table A1, columns 5-7).

Second, one could argue that if there is measurement error in calculating savings, then their coefficient would be biased. Similarly, including just last months' savings may be a more noisy measure of the true potential savings a customer could achieve. To alleviate these concerns, we recalculate savings for each customer using a moving average of her last three months and re-run our baseline results from Table 2. None of our previous results changes in any fundamental way, while the impact of overage increases slightly (Table A2).

Third, we also experiment by calculating an alternative measure of variance based on savings. Savings measure consumption variability and, as such, it might be useful to capture fluctuations in calling behavior. Estimated results are very similar to those previously obtained (Table A3 replicates the analysis in Table 3).

The picture that emerges from this evidence is one in which customers respond, possibly sequentially, to the information received from BM. If the message says that the customer is already on a plan with a good tariff (negative savings), the customer does not have any incentives to look deeper into her consumption pattern, and she stops there. If, instead, the customer receives notice that savings are possible, then she is inclined to look much closer at her behavior and at the contract. This is when she learns about overage, on top of savings, which then initiates the switching patterns that we described above. The consumer perceives overage as a loss, irrespective of the savings, and, thus, is much more likely to switch contracts.

Our results support prospect theory: we found loss aversion to be significant in determining consumers' choice to change plans, but we did not find bill variance to be a determinant of their choice. Consumers who could reduce losses by a certain amount relative to their salient point (monthly tariff) changed plans significantly more than consumers who could improve (gain) by the same amount without having experienced overage. We have established that the asymmetry between losses and gains can explain observed consumer behavior but that a uniform attitude towards risk in both losses and gains (an assumption central to expected utility theory) cannot explain customers' switching. Consumers' attitude towards risk was found to be in line with prospect theory: our consumers exhibit an appetite for risk (bill variance) when they are in the loss (overage) domain.

6. Conclusions

We have conducted an assessment of consumer behavior using individual data from UK mobile operators collected by a price comparison website. We showed that consumers who receive reminders about possible savings do respond and switch tariff plans. More interestingly, we also discussed how consumers employ their monthly fixed payment as a reference point in their choices. When they spend above this reference point, the resulting overage payment induces considerable switching. This central finding is very much in line with the Loss Aversion model of Kahneman and Tversky (1979) and is robust to several alternative interpretations and specifications.

We were also able to weigh how both risk and loss-aversion considerations affect choices in mobile telephony in a modern western economy: this is a high-stake industry affecting the majority of the population everywhere in the world. We find that risk aversion cannot explain consumers' switching, while loss aversion plays an important role.

Our results put the use of price-comparison sites in a new light. Regulators and competition authorities worldwide oversee price accreditation schemes for third-party price-comparison sites covering several industries – in addition to mobile phones – that still exhibit considerable uncertainty in patterns of consumption over time (e.g., banking, credit cards and insurance). The aim of these schemes is to increase consumer confidence about how to find the best price for the service they wish to purchase, and to increase market transparency by providing or facilitating expert guidance. Thaler and Sunstein (2008) propose the RECAP (Record, Evaluate, and Compare Alternative Prices) regulation that would require firms to let customers share their usage and billing data with third parties, such as BM, which could, in turn, provide unbiased advice about whether to switch to a competing provider.[36]

The emphasis of these proposals is almost invariably on savings – e.g., finding the most cost-effective tariff given a certain consumer profile. While this information is certainly useful for choice, we also show that savings are only a part of the story, and possibly a minor one. Hence, we introduce a note of caution on expert advisers that is different from any conflict-of-interest consideration (Inderst and Ottaviani, 2012) or from cases in which nudging may have adverse market equilibrium effects (Duarte and Hastings, 2012; Handel, 2013). We suggest that regulators hoping to rely on price-comparison engines to discipline market prices

[36] Without implying that nudging is always welfare-increasing

using shared data should first investigate what giving good advice means in a context with loss aversion. Consumers also switch for behavioral reasons that have little to do with savings, but that still could be consistent with optimal individual behavior.

In this paper, we have limited our analysis to the positive implications of behavioral economics – namely, on predicting switching behavior in the presence of loss aversion. Understanding the effect on social welfare is equally important. In particular, consumer switching is central to any competitive assessment of an industry. Developing a non-paternalistic method of welfare analysis in behavioral models is, however, a challenge. Following Chetty (2015), one possibility is to use revealed preferences in an environment in which agents are known to maximize their "experienced" utility (their actual well-being as a function of choices), which may differ from their "decision" utility (the objective to be maximized when making a choice).[37] The approach used in our setting is that the amount of savings is calculated mechanically by an optimizing algorithm; thus, most behavioral biases should vanish or at least be kept to a minimum. The fact that we still find a considerable role played by overage implies that loss aversion is of the utmost importance directly in the experienced utility and must be accounted for in any welfare assessment.

[37] An alternative approach is to follow structural modeling that specifies and estimates the structural parameters of a behavioral model. Grubb and Osborne (2015) follow this line to discuss the recent "nudge" adopted by the FCC (the US telecom regulator) of requiring bill-shock alerts for mobile phones (text messages warning when allowances of minutes, texts, or data are reached). They show that providing bill-shock alerts to compensate for consumer inattention can reduce consumer and total welfare because, most likely, firms will adjust their pricing schedule by reducing overage fees and increasing fixed fees.

References

Ater, Itai, and Vardit Landsman. 2013. "Do Customers Learn From Experience? Evidence From Retail Banking." *Management Science* 59(9): 2019–35.

Barberis, Nicholas C. 2013. "Thirty Years of Prospect Theory in Economics: a Review and Assessment." *Journal of Economic Perspectives* 27(1): 173–96.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics* 119 (1): 249–275.

Booth, Philip, and Stephen Davies. 2015. "Price Ceilings in Financial Markets," in Coyne, Christopher and Rachel Colyne (Eds.). *Flaws and Ceilings: Price Controls and the Damage they Cause*. Institute of Economic Affairs, London.

Camerer, Colin, George Loewenstein, and Matthew Rabin. 2004. *Advances in Behavioral Economics*. Princeton University Press, Princeton.

Chetty, Raj. 2015. "Behavioral Economics and Public Policy: A Pragmatic Perspective." *American Economic Review Papers and Proceedings* (forthcoming).

Cohen, Alma, and Liran Einav. 2007. "Estimating Risk Preferences From Deductible Choice." *American Economic Review* 97(3): 745–788.

Cox, D R. 1972. "Regression Models and Life Tables." *Journal of the Royal Statistical Society* 34(2): 187–220.

DellaVigna, Stefano. 2009. "Psychology and Economics: Evidence From the Field." *Journal of Economic Literature* 47(2): 315–72.

DellaVigna, Stefano, and Ulrike Malmendier. 2004. "Contract Design and Self-Control: Theory and Evidence." *Quarterly Journal of Economics* 119 (2): 353–402.

Duarte, Fabian, and Justine S. Hastings. 2012. "Fettered Consumers and Sophisticated Firms: Evidence from Mexico's Privatized Social Security Market." NBER Working Paper 18582.

Economides, Nicholas, Katja Seim, and V Brian Viard. 2008. "Quantifying the Benefits of Entry Into Local Phone Service." *RAND Journal of Economics* 39(3): 699–730.

Ericson, Keith M. Marzilli, and Andreas Fuster (2011) "Expectations as Endowments: Evidence on Reference-Dependent Preferences from Exchange and Valuation Experiments. " *Quarterly Journal of Economics* 126(4):1879–1907.

Fehr, Ernst, and Lorenz Götte. 2007. "Do Workers Work More if Wages Are High." *American Economic Review* 97(1): 298–317.

Fryer, Roland G, Jr., Steven D. Levitt, John List, and Sally Sadoff. 2012. "Enhancing the Efficacy of Teacher Incentives Through Loss Aversion." NBER Working Paper 18237.

Genakos, Christos, and Tommaso Valletti. 2011. "Testing the 'Waterbed' Effect in Mobile

Telephony." *Journal of the European Economic Association* 9(6): 1114–42.

Genesove, David, and Christopher Mayer. 2001. "Loss Aversion and Seller Behavior: Evidence From the Housing Market." *Quarterly Journal of Economics*, 116(4): 1233–60.

Grubb, Michael D. 2009. "Selling to Overconfident Consumers." *American Economic Review* 99(5): 1770–1807.

Grubb, Michael D. 2015. "Overconfident Consumers in the Marketplace." *Journal of Economic Perspectives* (forthcoming).

Grubb, Michael D, and Matthew Osborne. 2015. "Cellular Service Demand: Biased Beliefs, Learning, and Bill Shock." *American Economic Review* 105(1): 234–71.

Handel, Benjamin R. 2013. "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts." *American Economic Review* 103(7): 2643–82.

Heffetz, Ori, and John A. List. 2014. "Is the Endowment Effect an Expectations Effect?" *Journal of the European Economic Association* 12(5): 1396–1422.[Now published, title also changed]

Jiang, Lai. 2012. "The Welfare Effects of 'Bill Shock' Regulation in Mobile Telecommunication Markets." Working Paper.

Kahneman, Daniel. 2003. "Maps of Bounded Rationality: Psychology for Behavioral Economics." *American Economic Review*, 93(5): 1449–1475.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect Theory: an Analysis of Decision Under Risk." *Econometrica* 47(2): 263–292.

Kahneman, Daniel, Jack L. Knetsch, and Richard H. Thaler. 1990. "Experimental Tests of the Endowment Effect and the Coase Theorem." *Journal of Political Economy* 98(6): 1325–1348.

Kling, Jeffrey R., Sendhil Mullainathan, Eldar Shafir, Lee C. Vermeulen, and Marian V. Wrobel. 2012. "Comparison Friction: Experimental Evidence From Medicare Drug Plans." *Quarterly Journal of Economics* 127(1): 199–235.

Knetsch, Jack L. 1989. "The Endowment Effect and Evidence of Nonreversible Indifference Curves." *American Economic Review* 79(5): 1277–1284.

Kőszegi, Botond. 2014. "Behavioral Contract Theory." *Journal of Economic Literature* 52(4): 1075–1118.

Kőszegi, Botond, and Matthew Rabin. 2014. "A Model of Reference-Dependent Preferences." *Quarterly Journal of Economics* 121(4): 1133–65.

Inderst, Roman, and Marco Ottaviani. 2012. "How (not) to pay for advice: A framework for consumer financial protection." *Journal of Financial Economics* 105(2): 393–411.

Lambrecht, Anja, and Bernd Skiera. 2006. "Paying Too Much and Being Happy About It: Existence, Causes, and Consequences of Tariff-Choice Biases." *Journal of Marketing*

Research 43(2): 212–23.

Lambrecht, Anja, Katja Seim, and Bernd Skiera. 2007. “Does Uncertainty Matter? Consumer Behavior Under Three-Part Tariffs.” *Marketing Science* 26(5): 698–710.

List, John. 2003. “Does Market Experience Eliminate Market Anomalies?” *Quarterly Journal of Economics* 118(1): 41–71.

List, John. 2004. “Neoclassical Theory versus Prospect Theory: Evidence from the Marketplace. ” *Econometrica* 72(2): 615–25.

Miravete, Eugenio J. 2002. “Estimating Demand for Local Telephone Service with Asymmetric Information and Optional Calling Plans.” *The Review of Economic Studies* 69(4): 943–71.

Miravete, Eugenio J, and Ignacio Palacios-Huerta. 2014. “Consumer Inertia, Choice Dependence and Learning From Experience in a Repeated Decision Problem.” *Review of Economics and Statistics* 96(3): 524–537.

Ofcom. 2013. *Communications Market Report 2013*. Office of Communications, London.

Pope, Devin G, and Maurice E Schweitzer. 2011. “Is Tiger Woods Loss Averse? Persistent Bias in the Face of Experience, Competition, and High Stakes.” *American Economic Review* 101(1): 129–57.

Rabin, Matthew. 1998. “Psychology and Economics.” *Journal of Economic Literature* 36(1): 11–46.

Rabin, Matthew. 2000. “Risk Aversion and Expected-Utility Theory: a Calibration Theorem.” *Econometrica* 68(5): 1281–92.

Seim, Katja, and V Brian Viard. 2011. “The Effect of Market Structure on Cellular Technology Adoption and Pricing.” *American Economic Journal: Microeconomics* 3(2): 221–51.

Thaler, Richard, and Cass Sunstein. 2008. *Nudge: Improving Decisions about Health, Wealth, and Happiness*. Yale University Press, New Haven.

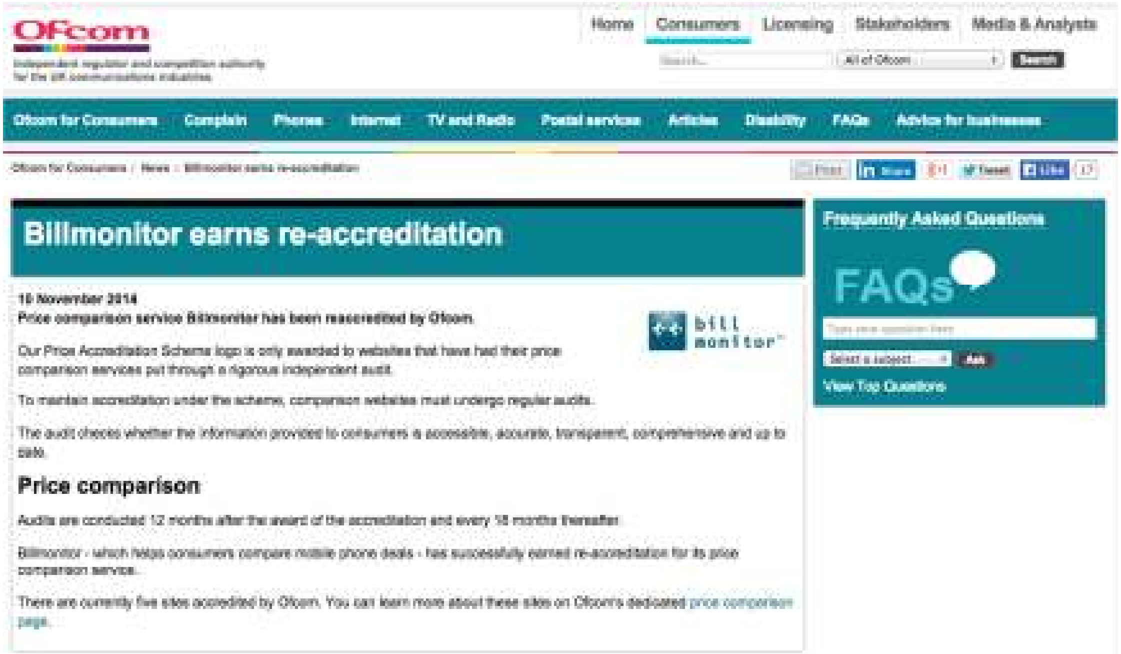
Tversky, Amos, and Daniel Kahneman. 1992. “Advances in Prospect Theory: Cumulative Representation of Uncertainty.” *Journal of Risk and Uncertainty* 5(4): 297–323.

NOT FOR PUBLICATION – REFEREE USE ONLY

Appendix A – The consumer experience with Billmonitor.com

In this annex, we present in various screen shots the consumer experience of registering and using BM's services. BM was created to provide impartial information and to help monthly paid mobile phone customers to choose contract that is best for them. BM was first accredited by Ofcom in 2009 and still receives accreditation (Figure A1). To safeguard its impartiality, BM neither receives advertising from any mobile operator nor allows for any kind of promotions on its website. It simply collects all available contract information from all UK mobile operators and tries to match each consumer's consumption pattern with the best available tariff.

FIGURE A1: BM's OFCOM RE-ACCREDITATION

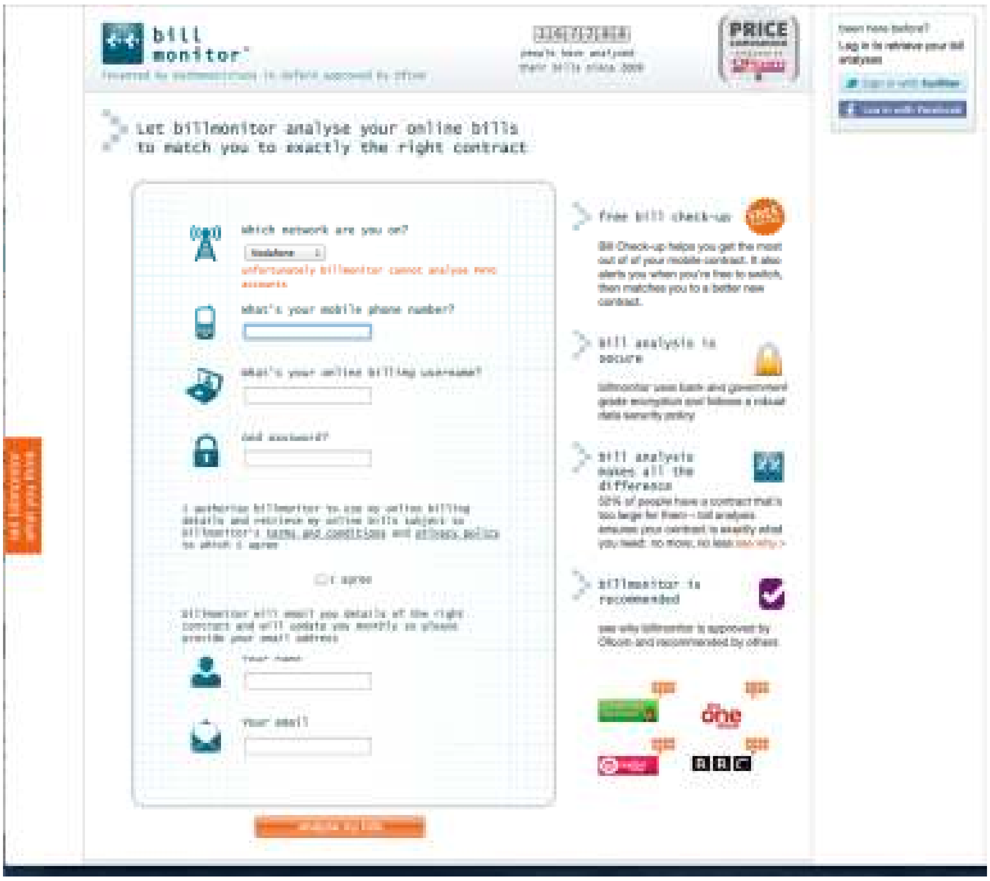


When a user visits the BM webpage, she is prompted to register in order to have her bills analyzed and to determine "*exactly* the right mobile contract" for her (Figure A2).

FIGURE A2: BM's HOME PAGE

If she chooses to have the BM engine analyze her bills, she is led to a page asking for her details (mobile operator, phone number, username and password and email), as shown in Figure A3.

FIGURE A3: BM's ANALYSIS PAGE



During the analysis of her bill, she is presented with a screen that informs her that BM searches through all possible contract combinations to find the "right" contract for her (Figure A4).

FIGURE A4: BM's CALCULATION SCREEN

Upon analysis of her bill, the user receives an email informing her of potential savings. This email is repeated monthly, the day after her bill is issued, as described in Figure 1 in the main text. Figure A5 shows an example of such an email.

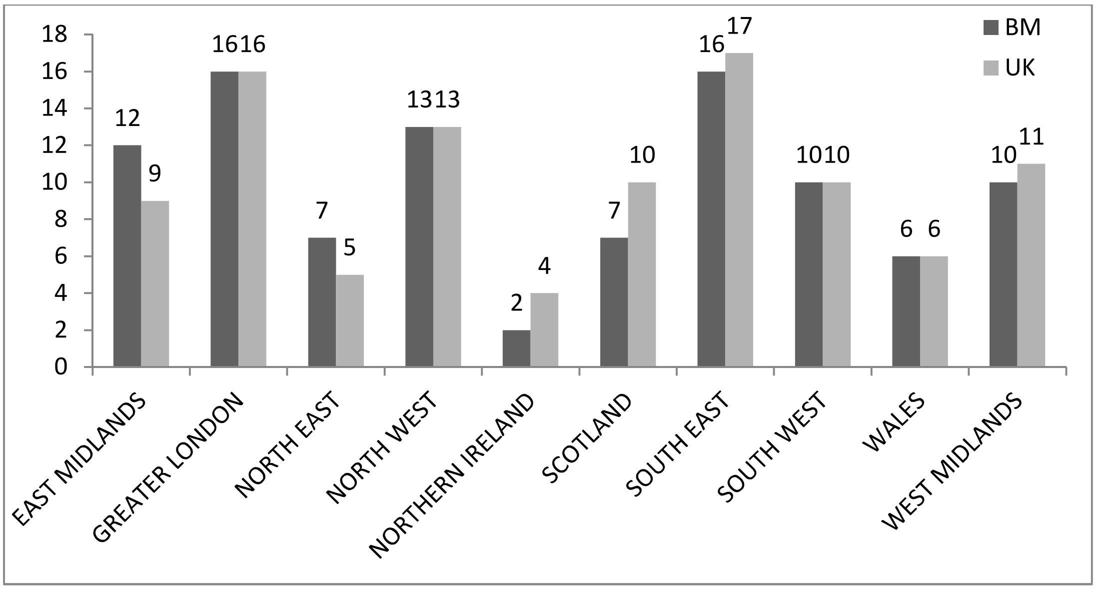
FIGURE A5: EMAIL SENT TO USERS INFORMING THEM OF POTENTIAL SAVINGS

Appendix B – Representativeness of the sample and summary statistics

In this annex, we discuss the representativeness of our sample and also provide some initial statistics on savings within our sample.

Figure B1 compares the geographic distribution of the population residing in the UK (ONS, 2011 census) with the customers registered with BM. As the figure shows, BM customers are well spread across the UK and match the actual population spread closely.

FIGURE B1: POPULATION DISTRIBUTION ACROSS UK REGIONS

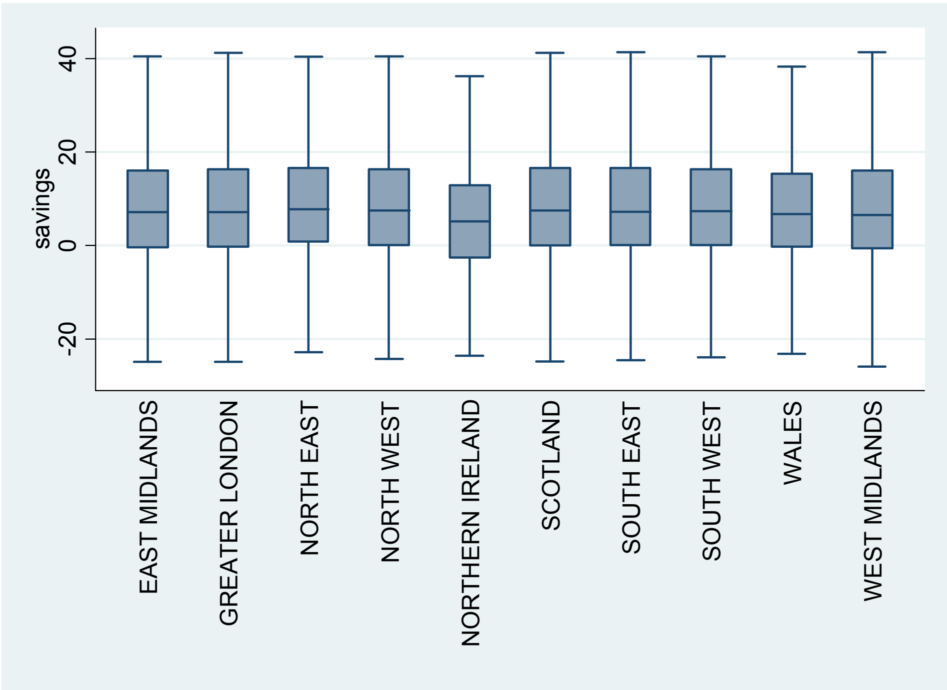


Notes: The graph above compares the percentage population distribution across regions in the UK and in the BM data.
Source: UK population distribution based on 2011 census, Office for National Statistics. BM population distribution based on the data provided by BM.

In all these different regions, consumers can realize savings by switching to different tariffs (Figure B2). Savings are, on average, positive across all regions, with the highest median savings in the North East (£7.2) and the lowest in Northern Ireland (£4).

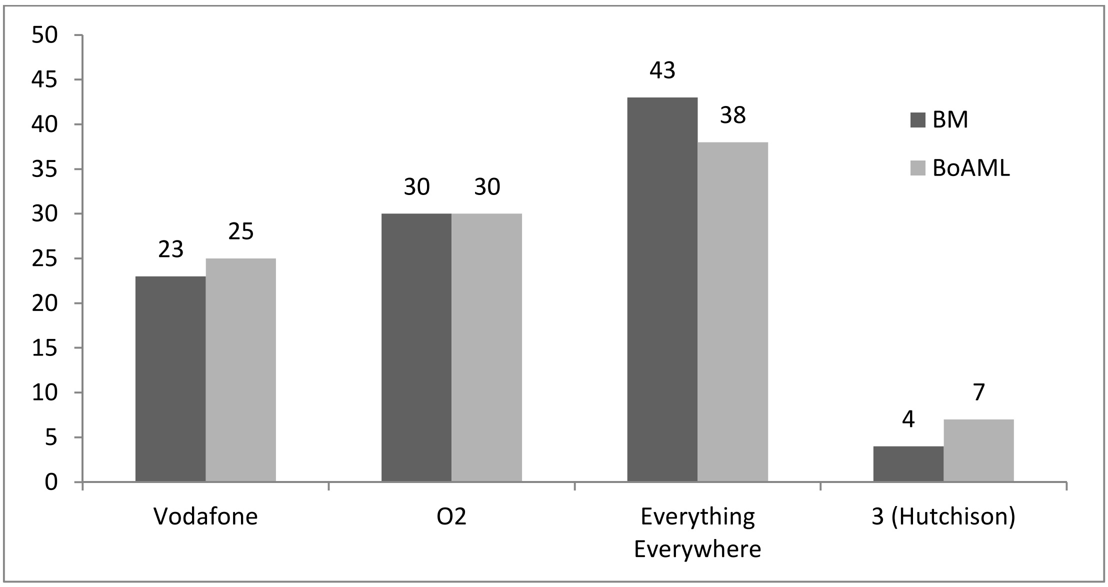
Figure B3 compares mobile operators' market shares in BM data with aggregate market information from the Bank of America Merrill Lynch (BoAML) dataset for 2012. Aggregate market shares are well tracked in the BM data, with the exception of Everything Everywhere (the merged entity of T-Mobile and Orange) that is slightly overrepresented and Three (Hutchison), which is slightly underrepresented. These discrepancies can be attributed to the fact that aggregate market shares also allocate to the licensed operators market shares of MVNOs (Mobile Virtual Network Operators) that do not have a spectrum license but rent airtime from the main licensed operators (they accounted for 8% of the total market in 2010-2012, mostly in the pre-paid segment; see Ofcom, 2013).

FIGURE B2: SAVINGS DISTRIBUTION ACROSS UK REGIONS



Notes: The graph above compares the savings distribution across different UK regions.
Source: Based on savings data provided by BM.

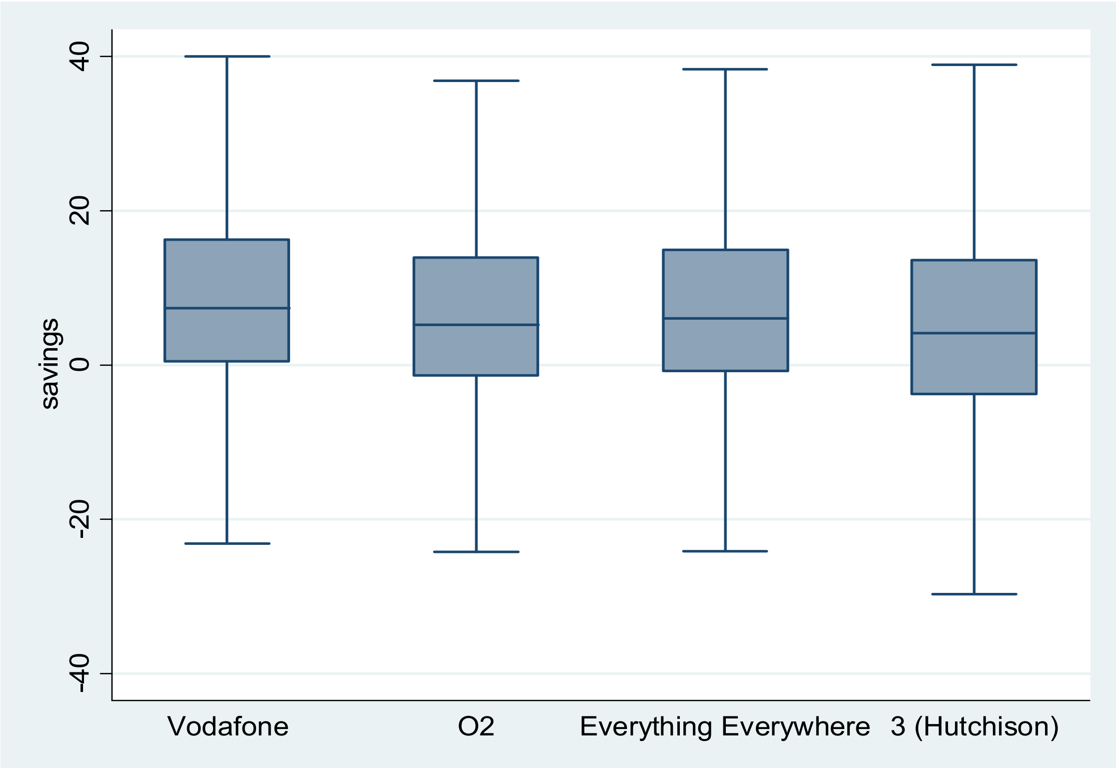
FIGURE B3: MOBILE OPERATORS' MARKET SHARES



Notes: The graph above compares the mobile operators' market shares from BoAML and BM data.
Source: Mobile operators market shares for 2012 based on the BoAML and BM datasets.

Customers across all operators can save, as Figure B4 demonstrates, with small but significant differences among them (highest median savings for Vodafone, £7.4, and lowest for Three, £4.1).

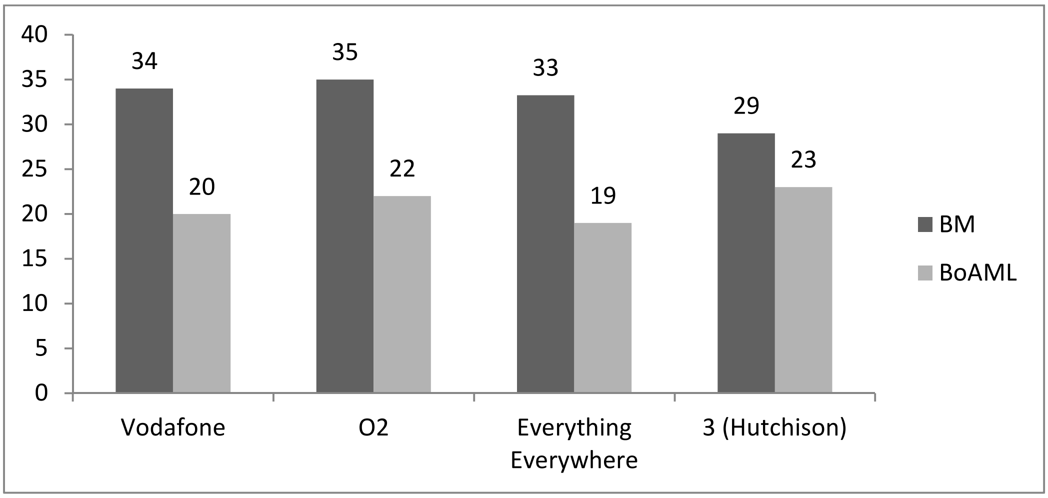
FIGURE B4: SAVINGS DISTRIBUTION ACROSS MOBILE OPERATORS



Notes: The graph above compares the savings distribution across mobile operators.
Source: Based on savings data provided by BM.

Figure B5 compares the average revenue per user (ARPU) in the BM sample with aggregate information obtained from the BoAML dataset for 2012. Given that BM has only post-paid customers, revenues are higher in the BM compared to the BoAML sample across all operators.

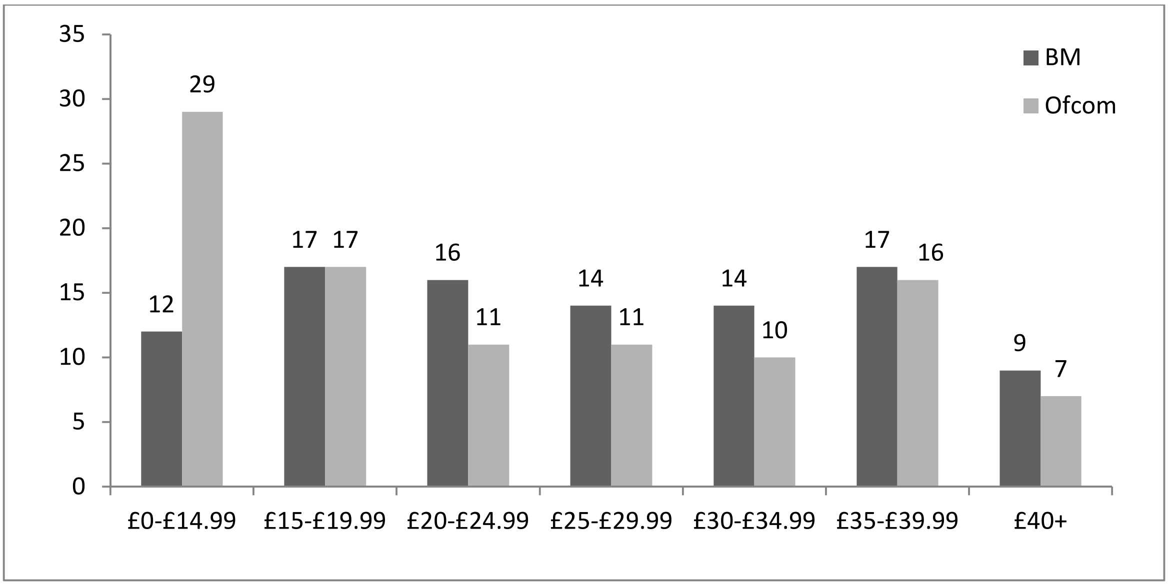
FIGURE B5: AVERAGE REVENUE PER USER ACROSS MOBILE OPERATORS



Notes: The graph above compares the mobile operators' average revenue per user from the BoAML and the BM data.
Source: Mobile operators' average revenue per user based on BoAML and BM data.

More interestingly, Figure B6 compares the distributions of consumers belonging to different tariff plans from the Ofcom[38] and the BM data. The two distributions are very similar, with the lowest tariff (£0-£14.99) being the only exemption.

FIGURE B6: MARKET SHARES BY TARIFF CATEGORY



Notes: The graph above compares the market shares by tariff category from the Ofcom report and BM data.
Source: Market share by tariff category based on the 2012 Ofcom Communications Market Report and BM data.

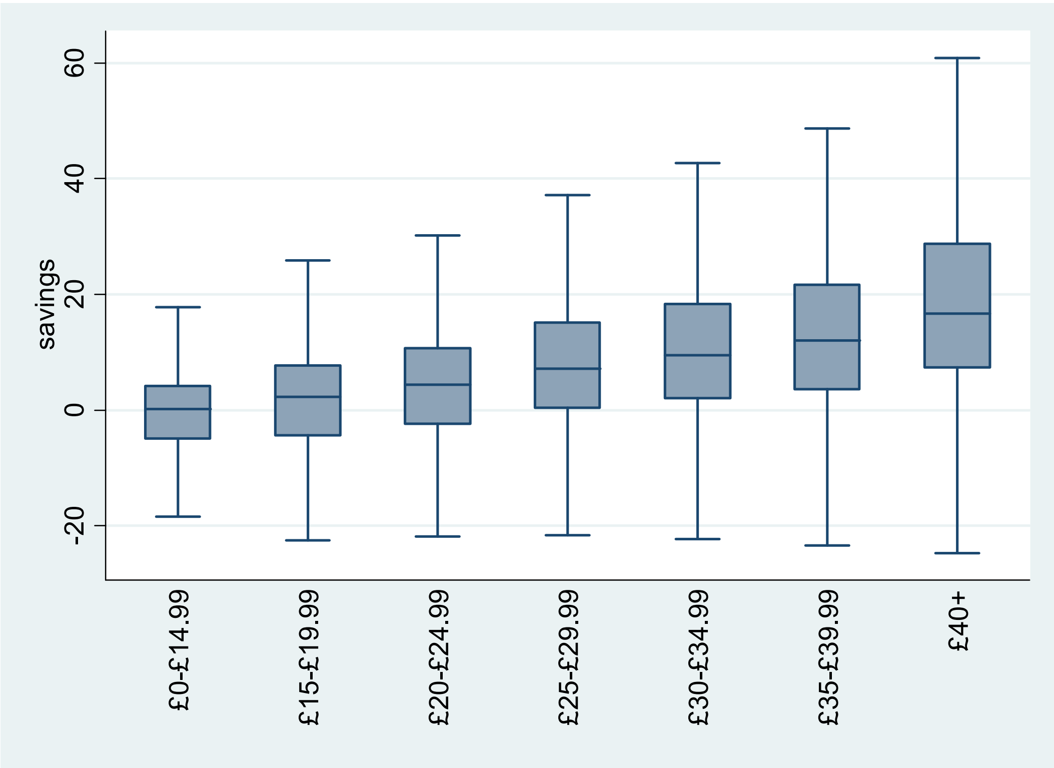
Savings can occur across any tariff category in the BM sample (see Figure B7). Unsurprisingly, more savings are available to those customers choosing larger and more expensive plans.

[38] Figure 5.75 from the 2012 Communications Market Report (p. 349).

Finally, if we compare the actual consumption, customers in the BM dataset send slightly more SMS (SMS per month: BM 251, Ofcom 201) and talk slightly more (minutes per month: BM 235, Ofcom 207) than the Ofcom 2012 report indicates, which also explains the higher ARPU.

Overall, the BM sample has a very good geographic spread across the UK and matches mobile operators' market shares and consumer tariff categories pretty closely. As it consists only of post-paid customers, these consumers seem to consume and spend more, on average, compared to the aggregate statistics, but without either any particular mobile operator or geographic bias.

FIGURE B7: SAVING DISTRIBUTION ACROSS TARIFF CATEGORY



Notes: The graph above compares the savings distribution across tariffs.
Source: Based on savings data provided by BM.

FIGURE 1: CONSUMER'S DECISION PROCESS

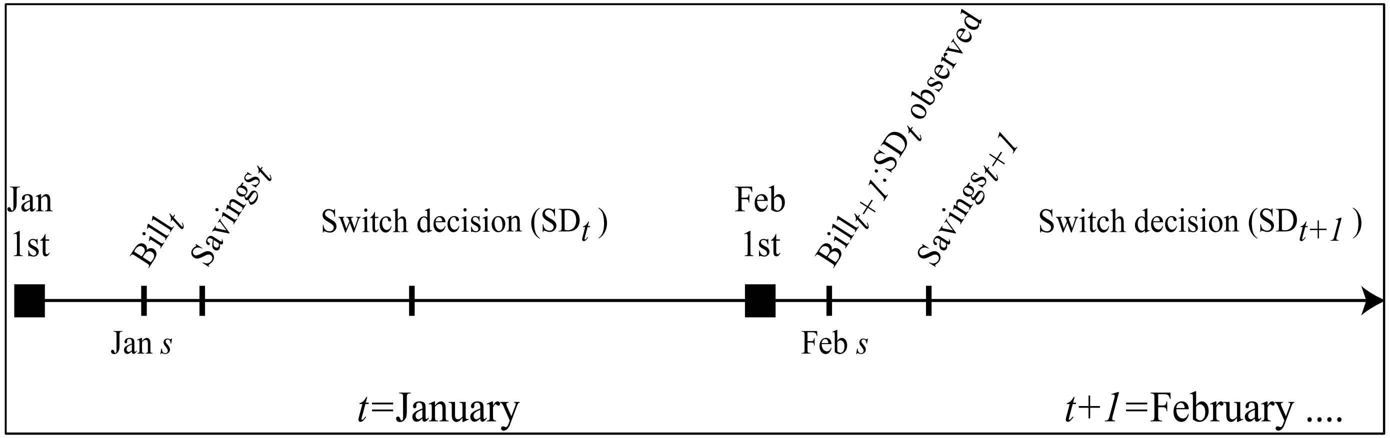
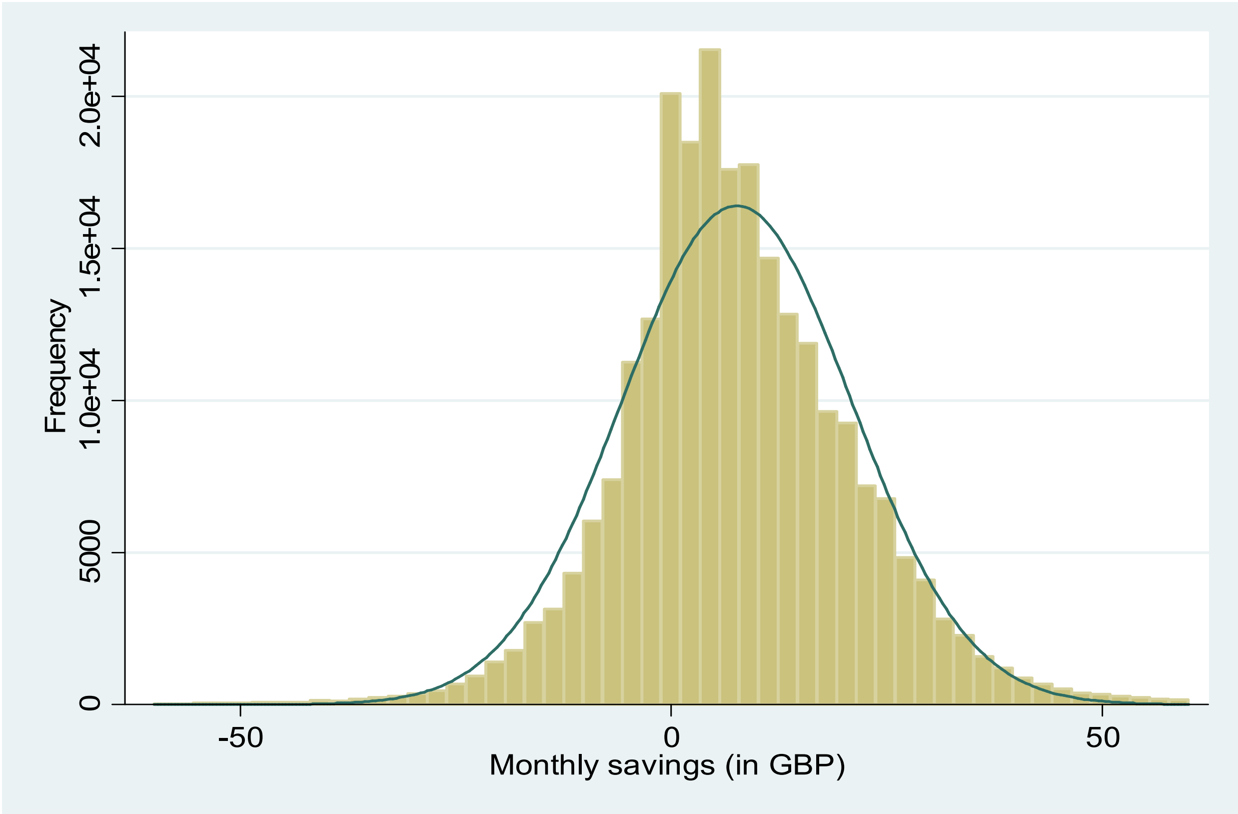
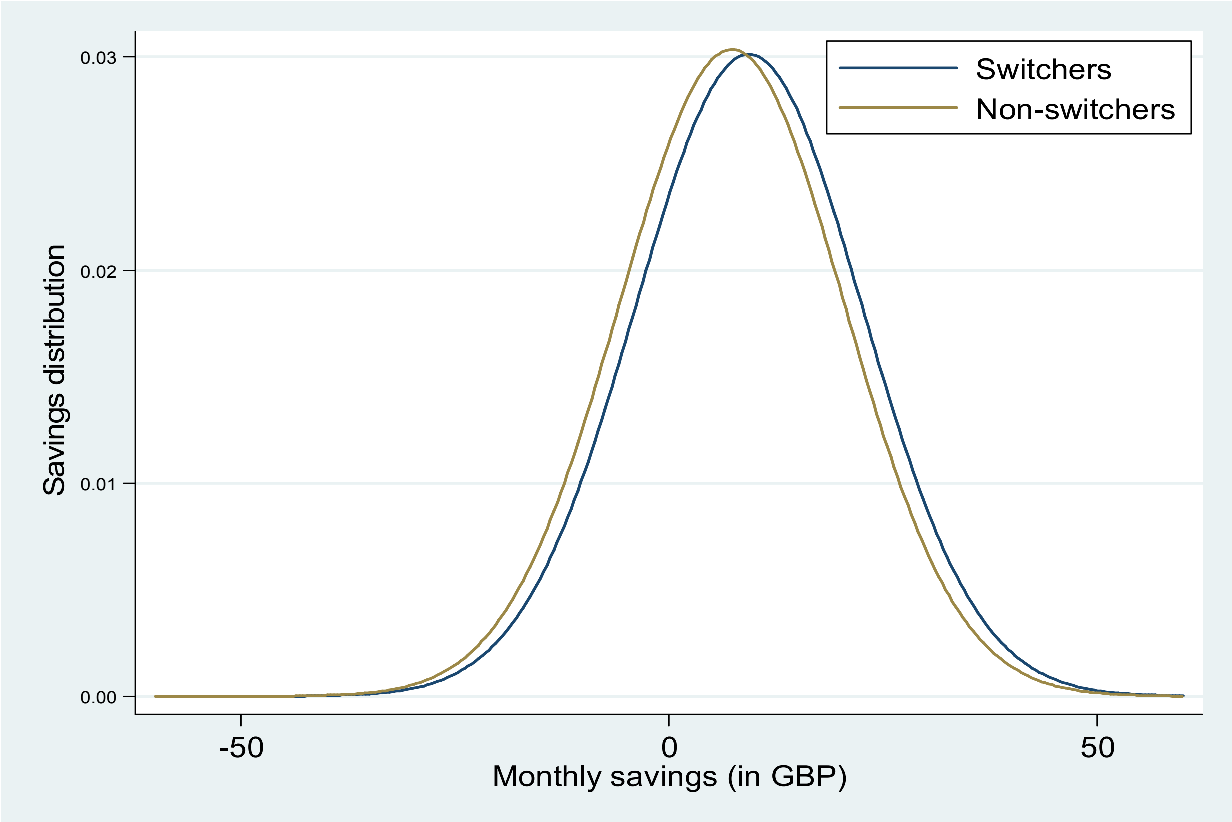


FIGURE 2: MONTHLY SAVINGS DISTRIBUTION



Notes: The figure presents information on the monthly savings distribution overlaid with a normal density curve.
Source: Authors' calculations based on data from Billmonitor.com.

FIGURE 3: SAVINGS DISTRIBUTION FOR SWITCHERS AND NON-SWITCHERS



Notes: The figure presents information on the monthly savings distribution of consumers who do not switch (non-switchers) and those who switch within operators (switchers) but before switching.

TABLE 1 - SUMMARY STATISTICS

Variable	Mean	Standard Deviation	10th percentile	50th percentile	90th percentile	Observations
Pr(switching)$_{it}$	0.080	0.271	0	0	0	186,515
Overage$_{i\ (t-1)}$	0.644	0.479	0	1	1	186,515
Savings$_{i\ (t-1)}$	7.409	31.743	-7.440	6.505	25.031	186,515
Bill Variance$_{i\ (t-1)}$	397.516	15366.34	0.039	6.764	295.239	112,323

Notes: The table above provides summary statistics on the key variables used in Tables 2, 3 and 4.
Source: Authors' calculations based on the the Billmonitor.com data.

TABLE 2 - THE IMPACT OF OVERAGE ON SWITCHING

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation method	OLS	FE	OLS	FE	FE	Logit (MLE)	Odds ratio	Proportional Hazard (MLE)	Hazard ratio
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$		pr(switching)$_{it}$	
Overage$_{i\,(t-1)}$	0.008***	0.014***			0.013***	0.075***	1.078***	0.086***	1.090***
	(0.001)	(0.002)			(0.002)	(0.020)	(0.021)	(0.018)	(0.019)
Savings$_{i\,(t-1)}$ (x 10^3)			0.188***	0.235***	0.230***	6.179***	1.006***	3.317***	1.003***
			(0.039)	(0.050)	(0.048)	(0.720)	(0.001)	(0.484)	(0.000)
Observations	186,515	186,515	186,515	186,515	186,515	186,515		186,515	
Adjusted/Within R^2	0.000	0.011	0.001	0.011	0.011				
Clusters	34,737	34,737	34,737	34,737	34,737	33,215		34,737	
Year-Month FE	no	yes	no	yes	yes	yes		yes	
Consumer FE	no	yes	no	yes	yes	no		no	

Notes: The dependent variable is the probability of switching to a different tariff plan within operator for consumer *i* in month *t*. Standard errors clustered at the consumer level are reported in parenthesis below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors’ calculations based on the the Billmonitor.com data.

TABLE 3 - LOSS AND RISK AVERSION

	(1)	(2)	(3)	(4)	(5)
Estimation method	OLS	FE	FE	FE	FE
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$
Overage$_{i\,(t-1)}$			0.015***	0.015***	0.016***
			(0.003)	(0.003)	(0.003)
Savings$_{i\,(t-1)}$ (x 10^3)			0.154***	0.156***	0.164***
			(0.042)	(0.044)	(0.047)
Bill Variance$_{i\,(t-1)}$ (x 10^6)	-0.004	-0.043**		0.012	0.036*
	(0.018)	(0.019)		(0.022)	(0.022)
Overage$_{i\,(t-1)}$ × Bill Variance$_{i\,(t-1)}$ (x 10^6)					-0.219***
					(0.080)
Observations	112,323	112,323	112,323	112,323	112,323
Adjusted/Within R^2	0.000	0.004	0.005	0.005	0.005
Clusters	21,271	21,271	21,271	21,271	16,494
Year-Month FE	no	yes	yes	yes	yes
Consumer FE	no	yes	yes	yes	yes

Notes: The dependent variable is the probability of switching to a different plan within operator for consumer *i* in month *t*. Standard errors clustered at the consumer level are reported in parenthesis below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on the the Billmonitor.com data.

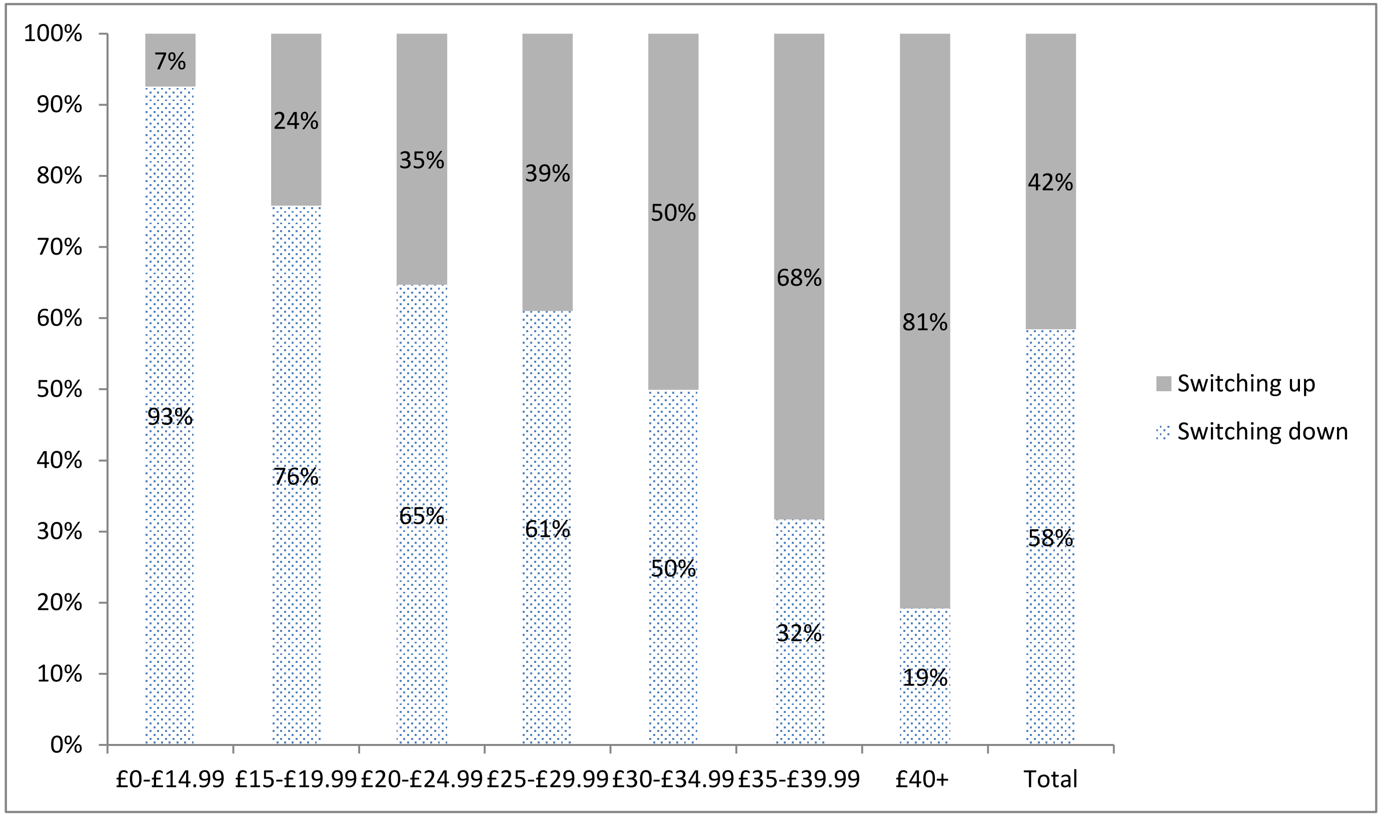
TABLE 4 - THE IMPACT OF OVERAGE ON SWITCHING - ROBUSTNESS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation method	FE	FE	FE	FE	FE	FE	FE
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$
Description	0<savings<3	3<savings<11	11<savings<35	Small and high overage	Include current operator in savings	Only current operator in savings	Consumers with negative savings
Overage$_{i\,(t-1)}$	0.016***	0.013***	0.009**		0.014***	0.009***	0.002
	(0.006)	(0.004)	(0.004)		(0.002)	(0.004)	(0.004)
Savings$_{i\,(t-1)}$ (x 10^3)	-0.224	4.598***	2.978***	0.225***	0.224***	0.155***	0.019
	(2.806)	(0.837)	(0.396)	(0.048)	(0.047)	(0.045)	(0.027)
Overage$_{i\,(t-1)}$ below the median				0.008***			
				(0.002)			
Overage$_{i\,(t-1)}$ above the median				0.022***			
				(0.003)			
Observations	19,546	51,130	60,757	186,515	183,624	70,324	48,953
Within R^2	0.007	0.007	0.008	0.012	0.011	0.012	0.007
Clusters	9,029	16,494	18,659	34,733	32,708	11,287	14,025
Year-Month FE	yes	yes	yes	yes	yes	yes	yes
Consumer FE	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the probability of switching to a different plan within operator for consumer *i* in month *t*. Standard errors clustered at the consumer level are reported in parenthesis below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on the the Billmonitor.com data.

NOT FOR PUBLICATION, REFEREE USE ONLY

FIGURE A1: SWITCHING DIRECTION SPLIT BY TARIFF CATEGORY



Notes: The figure presents information on the switching probabilities by Ofcom tariff category.
Source: Authors' calculations based on data from Billmonitor.com.

NOT FOR PUBLICATION, REFEREE USE ONLY

TABLE A1 - ROBUSTNESS - ALTERNATIVE SPECIFICATIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation method	Odds ratio	Odds ratio	Hazard ratio	Hazard ratio	FE	FE	FE
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$
Description	w/out variance	with variance	w/out variance	with variance	0<savings<3	3<savings<11	11<savings<35
Overage$_{i\,(t-1)}$	1.169***	1.166***	1.176***	1.174***	0.019***	0.015***	0.009**
	(0.035)	(0.035)	(0.033)	(0.033)	(0.007)	(0.005)	(0.005)
Savings$_{i\,(t-1)}$ (x 10^3)	1.007***	1.008***	1.005***	1.005***	0.171	3.665***	2.480***
	(0.001)	(0.001)	(0.001)	(0.001)	(3.263)	(0.939)	(0.525)
Bill Variance$_{i\,(t-1)}$ (x 10^6)		1.000		1.000	-0.804	0.247	-0.567
		(0.000)		(0.000)	(1.270)	(0.300)	(0.400)
Observations	112,323	112,323	112,323	112,323	12,726	31,856	33,758
Adjusted/Within R^2			0.000	0.004	0.006	0.004	0.006
Clusters	21,271	21,271	21,271	21,271	5,858	10,372	10,083
Year-Month FE	yes	yes	yes	yes	yes	yes	yes
Consumer FE	no	no	no	no	yes	yes	yes

Notes: The dependent variable is the probability of switching to a different plan within operator for consumer *i* in month *t*. Standard errors clustered at the consumer level are reported in parenthesis below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on the the Billmonitor.com data.

NOT FOR PUBLICATION, REFEREE USE ONLY

TABLE A2 - ROBUSTNESS - ALTERNATIVE MEASURE OF SAVINGS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation method	OLS	FE	FE	Logit (MLE)	Odds ratio	Proportional Hazard (MLE)	Hazard ratio
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$		pr(switching)$_{it}$	
Overage$_{i\,(t-1)}$			0.016***	0.160***	1.173***	0.165***	1.179***
			(0.003)	(0.030)	(0.035)	(0.028)	(0.033)
Savings$_{i\,(t-1)}$ (x 10^3)	0.208***	0.231***	0.227***	7.676***	1.008***	5.304***	1.005***
three month lagged moving average	(0.052)	(0.058)	(0.057)	(1.232)	(0.001)	(1.054)	(0.001)
Observations	112,323	112,323	112,323	112,323		112,323	
Adjusted/Within R^2	0.001	0.004	0.005				
Clusters	21,271	21,271	21,271	21,271		21,271	
Year-Month FE	no	yes	yes	yes		yes	
Consumer FE	no	yes	yes	no		no	

Notes: The dependent variable is the probability of switching to a different plan within operator for consumer *i* in month *t*. Standard errors clustered at the consumer level are reported in parenthesis below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on the the Billmonitor.com data.

NOT FOR PUBLICATION, REFEREE USE ONLY

TABLE A3 - ROBUSTNESS - ALTERNATIVE MEASURE OF VARIANCE

	(1)	(2)	(3)	(4)
Estimation method	OLS	FE	FE	FE
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$
Overage$_{i\,(t-1)}$			0.015***	0.015***
			(0.003)	(0.003)
Savings$_{i\,(t-1)}$ (x 10^3)			0.154***	0.156***
			(0.042)	(0.044)
Savings Variance$_{i\,(t-1)}$ (x 10^6)	0.005	-0.052		0.012
	(0.037)	(0.036)		(0.022)
Observations	112,323	112,323	112,323	112,323
Adjusted/Within R^2	0.000	0.004	0.005	0.005
Clusters	21,271	21,271	21,271	21,271
Year-Month FE	no	yes	yes	yes
Consumer FE	no	yes	yes	yes

Notes: The dependent variable is the probability of switching to a different plan within operator for consumer *i* in month *t*. Standard errors clustered at the consumer level are reported in parenthesis below coefficients: *significant at 10%; **significant at 5%; ***significant at 1%.
Source: Authors' calculations based on the the Billmonitor.com data.