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Is having an expert "friend" enough? An analysis of consumer switching behavior in mobile telephony

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Abstract
We present novel evidence from a large panel of UK consumers who receive personalized reminders from a specialist price-comparison website about the precise amount they could save by switching to their best-suited alternative mobile telephony plan. We document three phenomena. First, even self-registered consumers with positive savings exhibit inertia. Second, we show that being informed about potential savings has a positive and significant effect on switching. Third, controlling for savings, the effect of incurring overage payments is significant and similar in magnitude to the effect of savings: 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. We interpret this asymmetric reaction on switching behavior as potential evidence of loss aversion. In other words, when facing complex and recurrent tariff plan choices, consumers care about savings but also seem to be willing to pay upfront fees in order to get "peace of mind".

Keywords: tariff/plan choice, inertia, switching, loss aversion, mobile telephony
JEL Codes: D91; D12; D81; L96; M30

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1. Introduction

Across a range of everyday markets, consumers make recurrent tariff choices, often complex when facing a multitude of fees. Regulators are concerned that consumers fail to make optimal choices of suppliers, resulting in significant welfare costs. From recently deregulated markets, such as electricity, social security or healthcare, to more established ones, such as retail banking, insurance or telecoms, researchers have demonstrated inertia in consumers' behavior. The predominant thinking among policymakers and academics is that a significant impediment in consumer switching is related to information acquisition and evaluation. Providing information should thus be a powerful marketing and regulatory tool.

This has led, for example, Thaler and Sunstein (2008) to 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, which could, in turn, provide unbiased advice about whether to switch to a competing provider. In a similar spirit, Grubb (2015a), reviewing the evidence on why consumers in various markets struggle to choose the best price, puts forward as policy advice the provision or facilitation of expert guidance. Kling et al. (2012) demonstrate that simply making information available does not ensure consumers will use it and suggest that, by personalizing the necessary market information, consumers would be able to overcome their "comparison frictions" and switch more often to lower cost offers. The question emerging hence is: can a trusted "expert" friend, who gathers and analyzes all available market information and proposes the best available options just for you, help consumers make better decisions?

We present new evidence from a unique environment. Consumers in our setting have registered with a specialist mobile-comparison website, that is independent and accredited by the industry regulator, and receive personalized information about the exact amount they could save by switching to the optimal contract for them. The most efficient contract, interpreted as the cost-minimizing plan, is calculated for each consumer by an optimizing algorithm that takes into consideration past bills and consumption patterns and matches them with the best available tariff plans in the market. Hence, in contrast to other papers in the literature, consumers in our setting have unbiased and personalized information available to them *before* making any choice. Detailed information about the choice of tariff plans, consumption, and monthly payments of 60,000 mobile phone users in the UK between 2010 and 2012 was made available to us by the price-comparison website, making it possible to analyze consumer choices given the information available to them at the time, without imposing ex-post assumptions.

We document three phenomena. First, we present evidence that even consumers with personalized, expert information on optimal contracts exhibit significant inertia: 62% of customers, who receive information that they can realize positive savings by switching to an alternative plan, do not act on this advice, forgoing £186 savings per year per capita on average. Second, in a switching probability econometric framework, we show that potential savings are still a significant determinant of switching. Third, we find that, controlling for savings, switching is more likely if a customer has been charged *overage fees* in the previous month. Overage fees are defined as the additional amount of money a customer has to pay if she exceeds her allowance in a certain period. These results hold true also when we can account for brand and handset preferences, network quality, among many other factors that we observe in the dataset. Hence, although personalized expert advice certainly facilitates switching, it seems to be only a part of the story.

We explore various potential explanations for these findings. Our preferred interpretation is loss aversion, which asserts that losses relative to a reference point are more painful than equal-sized gains are pleasant (Kahneman and Tversky, 1979). Despite the overwhelming laboratory evidence,[1] relatively few field studies document this phenomenon, making some scholars question whether loss aversion and other behavioral biases are really relevant in ordinary consumers' choice in everyday markets (Levitt and List, 2009). 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.). Monthly rental payment provides a natural reference point. Customers who exceed their allowances 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 same amount by switching to a lower tariff.[2] We show that this implies a kink at the reference point that is statistically and economically significant and robust to several alternative interpretations and specifications. In addition, we document a differential risk attitude of individuals who, on average, are risk averse in the domain of gains and risk seekers in the domain of losses, resulting in an S-shaped behavior of their value function that is also consistent with prospect theory.

Our results put the debate on consumer inertia and information acquisition and utilization under a new light. Micro-founded models of consumer inertia and plan choice in various markets have been studied in a number of empirical papers that use demand estimates for counterfactual market policies (see, e.g. Handel, 2013; Polyakova, 2016; Ho et al., 2017; Heiss et al., 2016; Hortacsu et al., 2017). All these models use a two-stage framework, where consumers first

[1] There is a large body of literature summarizing the main theories of individual decision making in psychology and economics. Rabin (1998), Camerer et al. (2004), DellaVigna (2009), Barberis (2013), Kőszegi (2014) and Chetty (2015) provide excellent reviews of the evidence in the field.

[2] Kahneman (2003), in his Nobel acceptance speech, similarly remarked: "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."

search for available information and consider whether to switch or not, and then choose among alternative plans. Psychological costs associated with either inattention, confusion or status quo bias typically affect the first, but not the second, stage of choice. Hence, the underlying assumption in the literature is that search costs are possibly both the largest and most important sources of inertia. We provide novel evidence that, even after eliminating search and selection stage frictions (in our setting consumers self-register, know how much they can save, and which contract is the cost-minimizing one for them), consumers still exhibit significant inertia. In addition, we argue that behavioral micro-foundations, such as loss aversion, seem to affect not only consumers' decisions to switch but also directly which bundle to choose.

Our findings can also have important business and regulatory repercussions. For marketeers, we find that customers care about prices and would be attracted by efficient cost-minimizing plans, ceteris paribus. But there is more. We also document what, we argue, are behavioral traits in consumer preferences that lead them towards price structures that avoid unexpected departures above mental reference points. Extra margins can be made by firms in this space, as they can charge for offering customers over-inclusive plans for a fixed fee, which ultimately give customers "peace of mind" in their recurrent and complex tariff choices. In this sense, inertia and lack of switching should be revaluated, as it may represent not only lack of information and mistakes on the consumer side, but also part of their preferences and utility function. This is important for regulators and competition authorities overseeing price-accreditation schemes for third-party price-comparison sites worldwide, covering several industries (e.g., banking, electricity, 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. The emphasis of these proposals is almost invariably on savings, such as finding the most cost-effective tariff given a certain consumer profile. This information is certainly useful for choice, but we introduce a note of caution on expert advisers that differs 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; Grubb and Osborne, 2015b). We suggest that regulators hoping to rely on price-comparison engines to discipline market prices using shared data should also investigate what giving good advice consists of in a context accounting for loss aversion (Karle and Möller, 2020). Similarly, as many firms have also begun recommending pricing plans to their customers in order to retain them in a competitive landscape, encouraging customers to switch to cost-minimizing plans can backfire as, shown, e.g., by Ascarza et al. (2016).

This paper contributes to the existing literature in several ways. First, we add to the growing literature that studies consumers' decision making when faced with too many options, a phenomenon that has been characterized as "choice overload" (Diehl and Poynor, 2010; Iyengar and Lepper, 2000), or "status quo bias" (Samuelson and Zeckhauser, 1988), or "inertia" (Dube et al., 2010) or "the paradox of choice" in which "more is less" (Schwartz, 2004). Consumers' inertia has been documented in various product markets, including orange juice and margarine (Dube et al., 2010), laundry detergent (Osborne, 2011), health insurance (Abaluck and Gruber, 2011; Handel, 2013; Ho et al., 2017; Heiss et al., 2016), electricity providers (Hortacsu et al., 2017) or mobile tariff plans (Goettler and Clay, 2011; Miravete and Palacios-Huerta, 2014; Grubb and Osborne, 2015). The common thread in these papers is that costly information acquisition and the complexity of the market raise switching costs (Farrell and Klemperer, 2007) and make comparisons and switching more difficult. We show that even when consumers have unbiased and personalized information available before making a choice, they still exhibit significant inertia.

We also contribute to recent literature that explores the effect of the Internet as a tool in reducing search costs and making comparisons easier (see for example Brynjolfsson and Smith, 2000; Scott Morton et al. 2001; Brown and Goolsbee, 2002; and Ellison and Ellison, 2009). Adding to these papers, we provide evidence from a specialized price-comparison website that is both more sophisticated and accurate than a simple web search and hence possibly closer to the economists' ideal of search cost reduction.

In addition, we offer new evidence on how behavioral biases directly affect consumer choice using field data from a large sample in an advanced economy, similar in spirit to evidence from different markets presented by Busse et al. (2015) or Hastings and Shapiro (2013), and contributing to the literature on behavioral industrial organization (Grubb, 2015a). Relatedly, we add to the small but rising literature that provides evidence on mental accounting and loss aversion using field data, that includes Genesove and Mayer (2001), Mas (2006), Pope and Schweitzer (2011), Ater and Landsman (2013), Engström et al. (2015) and Tereyağoğlu et al. (2018). In our setting, consumers' knowledge of how much they can save in advance means we do not need to impose assumptions or ex-post inferences about consumers' mental representation or (mis)calculations of their contract's value or savings. Moreover, our data allow us to test directly whether consumers exhibit diminishing sensitivity with respect to savings both in the gains and the losses domain, a key feature of prospect theory that, to our knowledge, has not been tested before using field data.[3]

Finally, 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, and

[3] Our application of behavioral economics to cellular phones is different from the extant literature on overconfidence and flat-rate bias. 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).

that mobile operators have tried and tested their pricing schemes to optimize profits in a highly competitive industry.

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. Section 4 presents the empirical strategy and discusses the main results, alongside several robustness checks. Section 5 concludes.

2. Industry background 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 (owned by BT), and the latest entrant, Three (owned by Hutchison). They all offer their services nationally. In 2011 (midway through our sample), there were 82 million mobile subscriptions 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.

A regulator, the Office of Communications (Ofcom) regulates the industry. The regulator controls licensing (spectrum auctions) and a few technical aspects (e.g., mobile termination rates and mobile-number portability); otherwise, the industry is deregulated. Operators freely set prices for consumers.[4]

[4] 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.[5] Instead, Ofcom has supported the idea that information should let consumers make better choices, because consumers are more likely to shop around when information is available, making it easier 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.[6]

Based on Ofcom's (2013) report, the annual switching between operators (churn rate) varies between 12% and 14% for the years 2010-2012 that we cover in our sample. No data on within-operator switching are publicly available, because this information is privately held by operators. In the BM sample, we observe that some 31% 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 and consumer tariff categories, indicating it is representative

[5] 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).

[6] https://www.ofcom.org.uk/phones-telecoms-and-internet/advice-for-consumers/costs-and-billing/price-comparison. Note that Ofcom emphasizes the independence of these websites. In the BM case, no conflict of interest exists between the advice they provide and the choice consumers make, because the site neither sponsors nor accepts advertising from any mobile provider.

of contract customers rather than pre-paid phone customers. With this caveat in mind, we recall that these customers are consumers who self-register on a price-comparison site and hence are more price-conscious and likely more prone to switching. Therefore, any findings concerning behavioral aspects of consumer choices are likely to be lower in our sample compared to the general population.

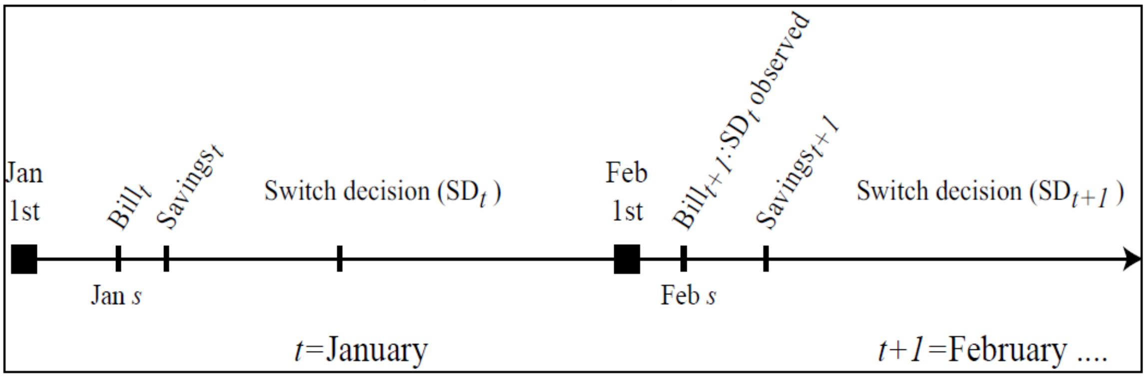
2.2 The consumer decision process

Upon users' registration with the website, BM attains access to their online bills. BM downloads past consumption patterns and bills, calculates potential savings over the user's last bill, and then informs the consumer of these potential savings.[7] The process is repeated monthly, as shown in Figure 1. In 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 to the user. Thus, on day s, the consumer receives her bill, followed by an email 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.[8] 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. Contrary to previous research, information about a reliable estimate of savings is directly

[7] To calculate savings and suitable contracts, BM builds scenarios for possible future calls (distinguishing between on and off-net or roaming), text, and data-usage 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. The cost for the chosen plan is then contrasted with the consumer's last bill to obtain savings relative to her last payment. All savings recommendations are made with respect to the users' stated preferences at the time they register (e.g., operator, contract length, handset).
[8] We do not have information on the suggested tariff plan, which is observed by the user.

available to the consumer and does not need to be calculated by the researcher. Consumers then act on their expected future behavior that is not observed by the researcher, in line with previous research.

FIGURE 1: CONSUMER'S DECISION PROCESS



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 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 total cost of the cheapest contract to the consumer, 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, a customer with positive savings will be prompted to see if she has exceeded the allowances and which fees for extras not included in the monthly bundle have been charged. Exceeding one's allowance is called *overage* in the cellular industry and happens when $B > R$. Note that for a customer with overage, B is experienced as a loss. So, for her, *savings* is a reduction of loss.

For a customer without overage, $B = R$, so no loss is experienced and *savings* is viewed as a potential gain over her last bill B. A customer can realise a given amount of savings by switching either above or below their current tariff, depending on their recent consumption patterns.

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

3. Data

For our analysis, we use information obtained from BM with more than 245,000 observations that contain monthly information on 59,772 customers from July 2010 until September 2012.[9] 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. Our main sample consists of consumers with positive savings that include their current mobile operator in their search.

Given that the data come from a price-comparison website on which consumers freely register, we first examine the sample representativeness (see Appendix B for details). 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.

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

[9] The panel is unbalanced. We observe a consumer for 5.4 months, on average, whereas the median consumer's life is 4 months. We explore this further in our robustness section.

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 we have reason to believe that customers who register with BM are those on larger tariff plans, because they can obtain bigger savings (Appendix Figure B6).

Overall, despite the fact that consumers self-register in this website, the sample seems to have 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.[10]

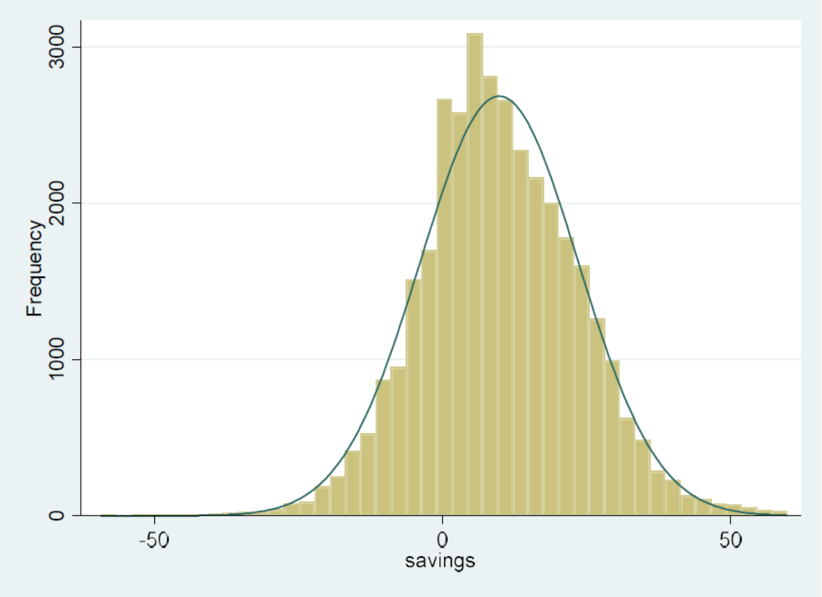
[10] We do not have information concerning the age or mobile experience of customers. When we control for the number of months that we observe each customer in our data, a proxy for contract tenure, the coefficient is not significant, indicating that, at least within our sample, "experience" does not make any difference for savings.

4. Analyzing consumer inertia and switching behavior

4.1 Descriptive analysis

Savings are calculated based on the user's last bills, so 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. We exclude negative savings from our main analysis, but we will use them later as a placebo test. Figure 2 plots the distribution of (monthly) savings for all consumers during their first month being registered in BM. The vast majority of customers have positive monthly savings (75%) indicating that there is a better tariff available that could save them money. Conditional on having positive savings, consumers could save on average £186 per year (£15.5 per month, which represents 57% of their monthly tariff) as we can see on the first row of the summary statics in Table 1, with the median being £157 (or £13.2 per month, which represents 51% of their monthly tariff).

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.

When conditioning savings on 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). Interestingly enough, savings increase significantly as one moves to higher tariff plans, ranked in different brackets by monthly rentals, following the definition of Ofcom (Table 1, column 1).

For data-availability reasons, we examine switching only across different tariff plans offered by the same operator.[11] Within-operator switching is important for two reasons. First, switching within operator is relatively easier than 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 frictions coming from 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, 31% 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.

For consumers with positive savings when they register in BM, an impressive 62% will not switch tariff plan. In other words, consumers who self-register in this specialized price comparison website and learn that they can save money by switching to another plan of their current operator, still exhibit significant inertia. Switching is evenly distributed geographically across the UK as well as across months within a year, with women switching slightly more often than men. In our sample there is switching in both directions: conditional on switching,

[11] A customer may leave the database either because she (received the information that she was looking for and) de-registers or because she switched to a new mobile operator (and hence BM cannot access her online account). Since we cannot distinguish between these cases, we focus on switching across tariff plans offered by her current operator.

TABLE 1 - SUMMARY STATISTICS

Tariff category	(1) Mean Savings	(2) Standard Deviation of Savings	(3) 10th percentile of Savings	(4) 50th percentile of Savings	(5) 90th percentile of Savings	(7) % Population who do Not Switch	(8) % Observations with Overage
All	15.5	14.3	2.8	13.2	29.6	62%	64%
£0-£14.99	8.1	8.8	0.8	5.1	20.4	53%	60%
£15-£19.99	10.1	11.2	1.9	7.8	19.1	63%	63%
£20-£24.99	12.1	11.5	2.4	10.5	21.4	63%	62%
£25-£29.99	14.3	13.6	2.9	13.7	24.4	63%	66%
£30-£34.99	16.9	13.3	3.6	16.4	28.5	64%	66%
£35-£39.99	18.4	13.3	3.8	18.2	31.1	64%	64%
>£40	23.8	19.9	6.1	21.9	40.1	56%	69%

Notes: The table provides summary statistics on the key variables used in our analysis. Categories of tariff plans as defined by Ofcom (2013).
Source: Authors' calculations based on the Billmonitor.com data.

roughly 59% of consumers switch to a lower tariff plan, whereas the remaining switch to a higher tariff plan.

Among consumers with positive savings, switchers (before switching) have higher monthly savings than non-switchers (£15.4 vs £14.8, p-value = 0.002). Hence, savings seem likely to be one of the factors triggering the decision to switch. Looking across tariff categories in Table 1(column 7), even though savings increase, the percentage of consumers switching is more or less stable, indicating that possibly other factors also play a role. One such potential candidate is overage.

Overage is very common: 64% of the customers in the sample experienced it (Table 1, column 8). If one looks at the actual difference between the bill (B) and the recurrent tariff cost (R), then the average amount of overage is £14, 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. Overage does not exhibit any particular relationship with different tariff plans, and even customers with negative savings experience it. Overage is 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, and so on. 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. Next, we subject these conditional statistics to more rigorous econometric tests.

4.2 Econometric evidence on switching behavior

To analyze consumer switching behavior while controlling for different confounding factors, we estimate the following econometric framework:

$$pr\ (switching)_{it} = \beta_0 + \beta_1 \cdot 1(overage)_{i(t-1)} + \beta_2 \cdot f\left(savings_{i(t-1)}\right) + d_i + d_t + \varepsilon_{it}. \quad (1)$$

The switching probability for individual i in 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(·) is an indicator function taking the value of 1 if $B > R$, and zero otherwise); *savings* are the monthly savings calculated by BM and communicated to the customer and $f(\cdot)$ is a flexible functional form that we assume to be linear in the parameters β_2. Notice that we correct for unobserved heterogeneity by controlling for fixed effects: d_i captures individual customer fixed effects, whereas d_t represents time (joint month-year) fixed effects. Thus, we control both for unobserved differences across customers and unobserved time shocks that may affect equally everybody. Finally, ε_{it} is the error term that captures all unobserved determinants of the switching behavior.

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, FE) logit model. Although such a model is better suited to the binary dependent variable, it is not ideal for our purposes, because the more appropriate FE logit model can be estimated only on a subsample of individuals with variation in the switching variable, that is, those who switch at least once during the period in which we observe them. This sample is non-representative 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 both right censoring (sample stops at September 2012) and left censoring (since consumers join BM at different points in time) and is flexible enough to allow for both time-invariant (e.g., mobile operator) and time-varying control variables (e.g., savings).

Table 2 reports the main results. When considered separately, 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 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, both variables retain their previously estimated magnitudes, indicating the processes of savings and overage are orthogonal to each other. More importantly, the economic impact of overage is comparable to that of savings. A £14 monthly savings, which is the average amount of savings for customers with positive monthly savings, increases the expected probability of switching by 2%, whereas if a customer’s monthly bill is higher than her tariff (where the average overage is also £14), the probability of switching increases by 1.5%.

Results are qualitatively unchanged when we use a logit model given the binary nature of the dependent variable. Column 6 reports the odds ratios: overage increases the odds of switching by 7%, whereas going from zero to average savings would increase the odds by 5.6%.[12]

Finally, the last column presents the estimated hazard ratio of the proportional hazard model. Again, we find that both overage and savings significantly increase the probability of switching, where overage increases the hazard of switching by 5.5%, whereas going from zero to average savings of £14 per month would increase the odds by 7% (column 7).

Notice that BM sends customers information about savings, expressed in both monthly (e.g., £10) and yearly format (e.g., £120). In fact, BM emphasizes the monthly savings in their email, which is also the format we use in our econometric analysis. These monthly savings are directly comparable to the overage paid the previous month. If the customer paid more attention to the annual equivalent of savings, which are mechanically larger than monthly, our findings on the role of overage are possibly more striking.[13]

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 the customer is to switch. This finding is consistent with 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.

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[12] Results using a conditional (consumer fixed effects) logit model are even stronger: overage increases the odds of switching by 22%, whereas going from zero to average savings would increase the odds by 25%. 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.

[13] If savings over time are discounted heterogeneously, and the discount factor is unknown but unrelated to other customer characteristics, we can think about this as measurement error in savings. We address this concern by re-estimating column 5 of Table 2 using log savings (results not reported here, available on request) and in section 4.3 by calculating moving averages of savings (see also Table A2 in the Appendix). None of our findings changes in any fundamental way.

TABLE 2 - WHAT AFFECTS SWITCHING BEHAVIOR?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation method	OLS	FE	OLS	FE	FE	Logit (Odds ratio)	Proportional Hazard (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$_{i\,(t-1)}$	0.004***	0.016***			0.015***	1.069***	1.055***
	(0.002)	(0.003)			(0.002)	(0.025)	(0.021)
Savings$_{i\,(t-1)}$ (x 10^3)			0.954***	1.480***	1.460***	1.004***	1.005***
			(0.081)	(0.141)	(0.140)	(0.001)	(0.000)
Observations	132,361	132,361	132,361	132,361	132,361	132,361	132,361
Consumers	28,992	28,992	28,992	28,992	28,992	28,992	28,992
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 Billmonitor.com data.

4.3 Additional insights and robustness tests

In this section, we first discuss the robustness of our findings in relation to sample selection or measurement issues. We then explore various alternative interpretations.

Self-selection due to flat-rate bias. Overage payments can be seen as unexpected payments customers try to avoid. In uncertain environments, risk-averse customers may select over-inclusive plans to avoid fluctuations in their payments, the so-called "flat-rate premium or bias" due to an insurance motive (Train et al., 1989; Lambrecht and Skiera, 2006; Herweg and Mierendorff, 2013). If the information about overage is related to such fluctuations, these customers then may also be more likely to switch, all else being equal.

To investigate possible self-selection, we divide the sample into small (0 < savings ≤ £3), medium (£3 < savings ≤ £11), and large savings (£11 < savings ≤ £35).[14] Customers who fall in the small-savings bracket are very good at predicting their behavior and do not select large buffers (otherwise, BM would also find large savings for them). Customers who have large savings may, instead, choose large buffers because of risk aversion. Yet, as columns 1, 2, and 3 of Table 3 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, experiencing overage leads them to switch contracts with a higher probability.[15] Comparing columns 1, 2, and 3, we note that the magnitude of the effect 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

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

[15] For customers with small savings, consumption closely matches their chosen plans. 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.

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.[16] Hence, as savings increase, overage continues to play a significant role, but the magnitude of its effect is smaller than that of savings.

Sample selection due to attrition. An alternative sample selection-problem may arise due to consumers' endogenous decisions to de-register from BM. For consumers who register, obtain the necessary information on savings and the best possible tariff, and then de-register, we cannot verify their subsequent behavior. One may argue that the fact that we do not know whether or not these consumers switch tariffs, may introduce a sample-selection bias. We address this concern in two ways. First, we randomly select a given year-month and keep only consumers (and their observations beforehand) who are alive during that month. Column 4 in Table 3 reports the results from our baseline specification when we follow this procedure and truncate the data in August 2012.[17] Results are qualitatively unchanged for both overage and savings. Second, in column 5 of Table 3, we re-estimate our baseline model using information only on the first three months from every consumer, in order to reduce to the minimum our consumers' time window within which they can deregister.[18] Note that using only the first three months from each consumer imposes a very strict hurdle, in that consumers should react immediately when they receive the necessary information. Column 5 seems to confirm this idea, because the coefficient on overage is slightly larger than our benchmark estimates in

[16] 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.
[17] This date was randomly chosen within 2012 with the aim to have enough data beforehand for each customer selected; results are robust to alternative selections.
[18] Three months is the shortest duration that we can impose given our lagged independent variables and the fixed effects.

Table 2, column 5.[19] Given that BM consumers self-register and hence are looking for better deals, perhaps the finding that they are ready to act almost immediately is not surprising.

Overage intensity. Next, we look 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 3, column 6, shows that the higher the overage, the more likely the consumer is to switch, while still controlling for the magnitude of savings. This finding seems to indicate that not just overage, but also its magnitude, 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, in line with the evidence in Grubb and Osborne (2015).

Contract constraints. Recall that, when consumers register with BM, they are asked to express their preferences related to the operator 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, BM looks at the universe of available tariffs. Switching between operators can be more difficult than switching within an operator, because additional costs may be involved. So far, we selected consumers who explicitly include their current operator in their search. In column 7, 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.

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 because

[19] Table A1, column 1 in the further robustness section of the Appendix repeats the exercise, keeping consumers' first five months (which is above the median and slightly below the mean lifetime of consumers in our data) and provides similar results.

TABLE 3 - WHAT AFFECTS SWITCHING BEHAVIOR? - ROBUSTNESS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation method	FE	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)$_{it}$	pr(switching)$_{it}$
Description	0<savings<3	3<savings<11	11<savings<35	Attrition corrected August 2012	First three months only	Small and high overage	Only current operator in savings	Consumers with negative savings
Overage$_{i\,(t-1)}$	0.017***	0.013***	0.011***	0.018***	0.039***		0.012***	0.001
	(0.006)	(0.004)	(0.004)	(0.003)	(0.008)		(0.004)	(0.004)
Savings$_{i\,(t-1)}$ (x 10^3)	0.253	4.845***	2.113***	1.444***	1.084***	1.410***	1.589***	0.017
	(2.876)	(0.819)	(0.295)	(0.146)	(0.408)	(0.145)	(0.230)	(0.027)
Overage$_{i\,(t-1)}$ below the median						0.009***		
						(0.003)		
Overage$_{i\,(t-1)}$ above the median						0.026***		
						(0.003)		
Observations	18,743	49,248	62,896	77,979	43,547	132,361	47,333	47,500
Consumers	8,850	16,197	18,936	15,977	26,920	28,992	9,647	14,002
Year-Month FE	yes	yes	yes	yes	yes	yes	yes	yes
Consumer FE	yes	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 Billmonitor.com data.

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), because 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 prompted to take a closer look at their bills, and thus they do not notice overage. Hence, we would not expect these customers to react either to their savings or to their overage information. In the last column of Table 3, we find that neither coefficient is statistically significant.

Finally, in Appendix C we provide further robustness tests of our results in relation to sample selection due to truncation, controlling for changes in mobile operators' strategies, controlling for further overage lags, and accounting for measurement error in savings.

4.4 Possible interpretations and discussion

Consumers in our setting: a) exhibit inertia despite significant positive savings, and, b) seem to respond equally to overage and to savings when they decide to switch. In what follows, we try to interpret this behavior through the lenses of different theories.

Starting with consumer inertia, the typical micro-foundations considered in the literature are inattention, preferences and product differentiation, or switching costs. In our setting it is hard to argue that consumers are inattentive: they self-register to a specialized price comparison website and receive personalized information, on top of the monthly bill that they receive from their mobile providers. Brand preference is typically modelled in the literature as added utility related to a particular brand or seller. Since here we are examining within operator switching, brand preference is irrelevant. However, one may still argue that there could be some kind of psychological status quo bias with respect to the particular tariff plan chosen. Although we cannot disprove this interpretation, we find more compelling to rationalize their behavior in terms of switching costs. From a rational point of view, the non-switching behavior can be rationalized by a high opportunity cost of time. Alternatively, from a psychological point of view, the hassle or negative utility related to the process of switching leads these customers to ignore the savings information provided by BM. If this interpretation is correct, it highlights the importance of switching costs (Farrell and Klemperer, 2007), or of the default effects (DellaVigna, 2009), over and beyond the issue of collecting and analyzing the appropriate market information.

The second phenomenon is much more challenging to interpret. The finding of asymmetric reaction to overage echoes previous results in the literature, such as Narayanan et al. (2007), who find that consumers in a measured fixed-line telephony plan detect mistakes and switch more often, or Ater and Landsman (2013), who find that customers who incur higher surcharges have a greater tendency to switch in a retail bank environment. However, in contrast to those papers, consumers in our setting know exactly how much they can save *before* making a choice. So, the fact that overage matters *conditional* on savings moves us beyond the conclusions of the previous papers, of drawing one's attention or of learning about mistakes in tariff choices.

Loss Aversion and Mental Accounting. One potential explanation of the results in Tables 2-3 is that of loss aversion or, more generally, of 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 à la Koszegi and Rabin (2006, 2007) based on monthly fees and distinguish between within-budget savings and overage losses. We find that customers prefer avoiding losses to obtaining gains, which is indeed the central prediction of the theory of loss aversion.

This can be seen by recalling the main result we have estimated. The probability of switching captures a consumer's utility from switching for any given level of savings. This differs between consumers with overage and consumers who consume under their allowances. This can be seen more formally in the following equation:

$$U(switching|savings) = \begin{cases} a_u + d \cdot savings, & \text{if overage} = 0 \\ a_o + d \cdot savings, & \text{if overage} > 0 \end{cases} \tag{2a}$$

In (2a), $a_i, i = o, u$ depicts the intercepts from the regression of switching on savings for the two groups (overage o, and no overage u). This is depicted in Figure 3a. The difference of the propensity to switch between the two groups is captured by the difference in the intercepts $(a_u - a_o)$. For a discussion of how equation (2a) relates to the standard Prospect Theory utility function, see Appendix D.

Prospect theory provides us with a further testable implication. According to Kahneman and Tversky's (1979) utility, presented in Figure 3b, consumers would exhibit risk aversion in gains and a risk-loving attitude in losses. This feature of diminishing sensitivity both in gains and losses can be captured by the convexity/concavity of the utility. Therefore, we also estimate a more general nonlinear model that allows us to test for the consumers' risk attitude:

$$U(switching|savings) = \begin{cases} a_u + f(savings), & \text{if overage} \leq 0 \\ a_o + f(savings), & \text{if overage} > 0. \end{cases} \tag{2b}$$

If $f(savings)$ is concave, this implies that consumers exhibit diminishing sensitivity with respect to savings both in the gains and the losses domain, or, in other words, consumers would exhibit risk aversion in gains and risk-loving attitude in losses, another key feature of prospect theory.

Table 4 reports the results: column 1 estimates a simple OLS regression to test the effect of savings and its squared term on switching. The coefficient of *savings* continues to be positive and significant, whereas the coefficient on $savings^2$ is negative and statistically significant, in line with the theoretical prediction regarding consumers' diminishing sensitivity. Column 2 repeats the exercise, controlling for consumer and year-month fixed effects. Both coefficients remain significant and increase in magnitude. Column 3 introduces also the effect of overage on switching for the same customer-months. The magnitude of the coefficient on overage obtained previously in Table 2, column 5, remains unchanged.

Having argued that consumers overall exhibit a diminishing sensitivity with respect to savings, in column 4, we include the interaction of both savings variables with overage to see whether this behavior is true for consumers in the gain as well as the loss domain. For consumers in the gain domain (when *overage* = 0), savings exhibit diminishing sensitivity with both coefficients being statistically significant. The coefficient on $savings^2$ is such that the maximum of the function[20] for these consumers is at £180; hence, the average savings are well to the left of this point, implying the utility function is on the increasing part. Similarly, consumers in the loss domain (when *overage* = 1) also exhibit diminishing returns on savings (coefficient on *savings* ($\times 10^3$) = 1.951, coefficient on $savings^2(\times 10^6)$ = -3.190), with the maximum for these consumers being at £305 (so consumers are also in the increasing part of the utility curve). Hence, consumers in our sample exhibit a risk-loving attitude in the domain of losses (Figure 3b). Diminishing sensitivity in both gains and losses is in line with the familiar S-shaped value function from prospect theory (see Appendix D), whereby individuals are risk-averse in the domain of gains and risk-loving in losses.[21]

To test the robustness of the diminishing returns on savings, we also experimented with a semi-parametric version of our estimation framework. Instead of assuming a concave function for

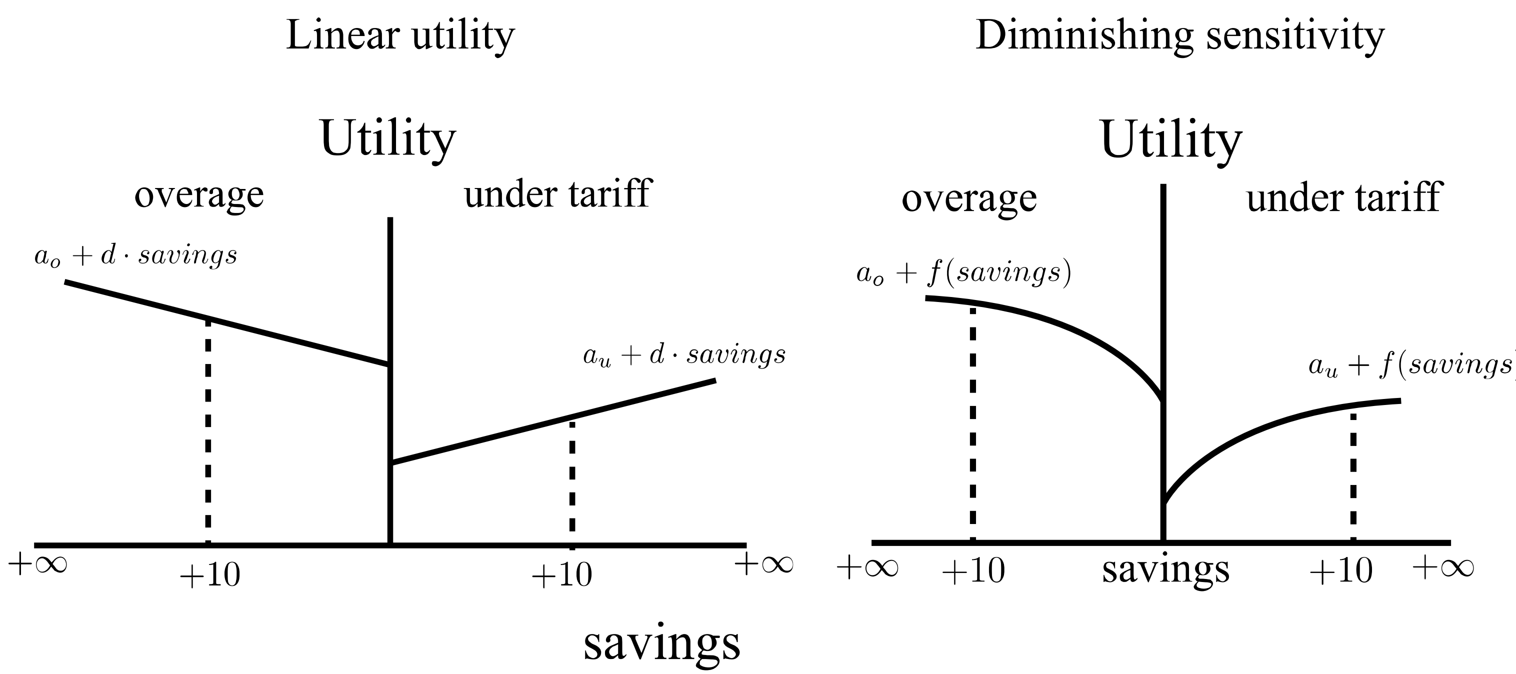
[20] The maximum of the function is achieved at the coefficient on savings over twice the absolute value of the coefficient on $savings^2$ (e.g., $[3.808/(2*10.600)]*10^3 \approx 180$).
[21] Note that Table 4, column 3 corresponds to Figure 3b, whereas in Table 4, column 4 we relax the common curvature assumption.

savings, we split savings into six equidistance brackets (£0-£5, £5-£10, £10-£15, £15-£20, £20-£25, and above £25) and introduce binary indicators (and their interactions with overage) into our estimated equation. Appendix Table A3 presents the results. Both overall (column 1) and across the two domains of gains and losses (column 2), the conclusion of diminishing returns remains qualitatively unchanged.

Although we have no direct evidence on how customers read the notices they receive from BM, the picture that emerges from this evidence seems to suggest that customers respond, possibly sequentially, to the information received from BM. If the message says 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, she is inclined to look much more closely at her behavior and at the contract. At this point, she learns about overage, on top of savings, which then initiates the switching patterns we described above. The consumer perceives overage as a loss, conditional on savings, and, thus, is much more likely to switch contracts.

Limited Attention and Saliency. One may argue that an overage payment can trigger attention, then customers would check their bills and other mobile plans more carefully and hence they would be more likely to switch. In this line of thought, overage is really capturing limited attention rather than loss aversion. We believe that this is a plausible argument which is not borne in our data, for two reasons. First, if the tendency to switch, following overage payments, is saliency à la Bordalo et al. (2013), then the ratio of overage to the fixed tariff payment should capture saliency. However, when we introduce this ratio $(Overage)_{i(t-1)}/(Tariff)_{i(t-1)}$ in our baseline specification, its coefficient is statistically not significant (p-value = 0.237) indicating again that the impact of overage is stronger on the extensive rather than the intensive margin (results are not shown to save on space, but are available from the authors). Second,

FIGURE 3: LOSS AVERSION IN BM's CONTEXT



(a)

(b)

TABLE 4 - SWITCHING BEHAVIOR AND RISK ATTITUDE

	(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***	0.034***
			(0.003)	(0.004)
Savings$_{i\,(t-1)}$ (x 10^3)	1.233***	2.298***	2.266***	3.808***
	(0.098)	(0.177)	(0.176)	(0.281)
Savings$^2_{i\,(t-1)}$ (x 10^6)	-2.000***	-4.150***	-4.090***	-10.600***
	(0.752)	(1.010)	(1.000)	(1.390)
Overage$_{i\,(t-1)}$ × Savings$_{i\,(t-1)}$ (x 10^3)				-1.857***
				(0.288)
Overage$_{i\,(t-1)}$ × Savings$^2_{i\,(t-1)}$ (x 10^6)				7.410***
				(1.560)
Observations	132,251	132,251	132,251	132,251
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 Billmonitor.com data.

the fact that consumers self-register in our setting, implies that they are likely to be actively looking for better deals, making the limited attention interpretation possibly less appealing in this setup.

5. Conclusions

We have assessed consumer behavior using individual data from UK mobile operators collected by a specialized price-comparison website. We find that consumers exhibit significant inertia, even consumers who self-register and receive personalized information on how much they can save. For those consumers who respond to reminders about possible savings, the amount of savings increases the probability of switching tariff plans. We also discuss how consumers seem to employ their monthly fixed payment as a reference point in their choices. When they spend above this reference point, the resulting overage payment induces sizable switching. We discuss how 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.

The case of the mobile phone industry is of particular interest, because mobile phones are ubiquitous and people spend a considerable amount of money on them. Our findings on consumer inertia and mental accounting could be 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, 2015b).

Although we do examine consumers’ post-switching behavior, we do not attempt to evaluate the optimality of their decisions, and refrain from making welfare claims. While we conduct an analysis of the determinants of consumer switching, understanding its effect on firms' profits and social welfare is of equal importance and left for further research. Developing a non-paternalistic method of welfare analysis in behavioral models poses several challenges. Following Chetty (2015), one possibility is to use revealed preferences in an environment where agents 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).[22] Our setting is possibly one where the amount of savings is calculated by an optimizing algorithm, minimizing cognitive biases associated with switching decisions. The fact that we still find a considerable role of overage suggests that loss aversion is of importance directly in the experienced utility of consumers, and therefore should be taken into account as one of the "primitives" informing consumer choice.

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[22] An alternative approach is to follow structural modeling that specifies and estimates the structural parameters of a behavioral model as in, e.g., Tereyağoğlu et al. (2018). Grubb and Osborne (2015) follow this line to discuss the "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.

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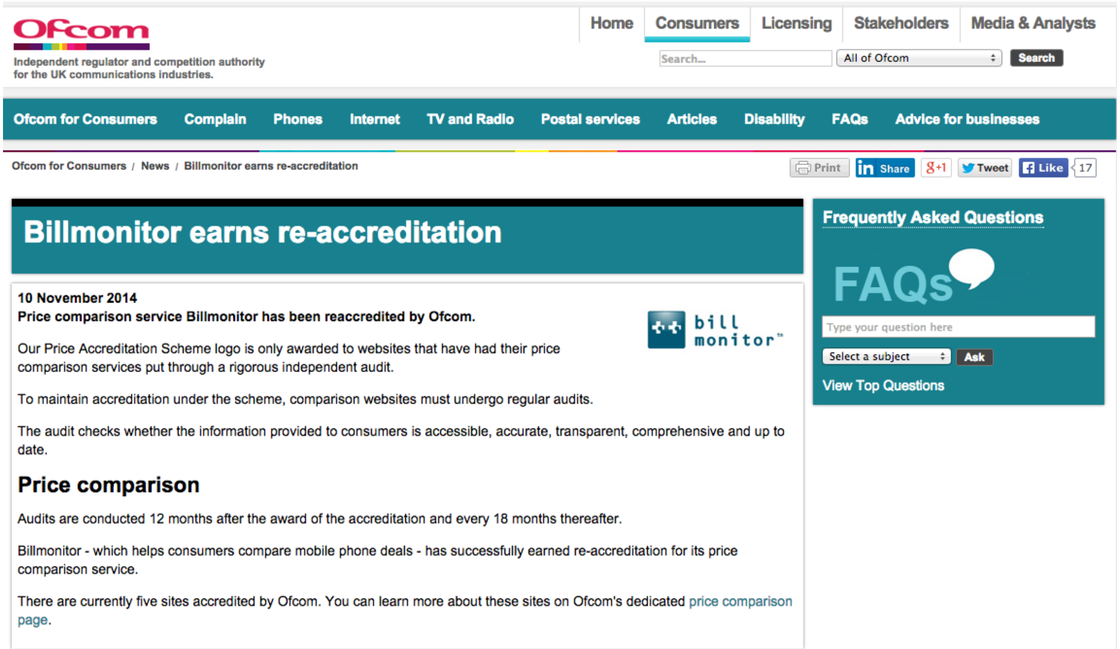
Web Appendix

Appendix A – The consumer experience with Billmonitor.com

In this annex, we present in various screenshots 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 the 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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Billmonitor earns re-accreditation

10 November 2014

Price comparison service Billmonitor has been reaccredited by Ofcom.

bill monitor

Our Price Accreditation Scheme logo is only awarded to websites that have had their price comparison services put through a rigorous independent audit.

To maintain accreditation under the scheme, comparison websites must undergo regular audits.

The audit checks whether the information provided to consumers is accessible, accurate, transparent, comprehensive and up to date.

Price comparison

Audits are conducted 12 months after the award of the accreditation and every 18 months thereafter.

Billmonitor - which helps consumers compare mobile phone deals - has successfully earned re-accreditation for its price comparison service.

There are currently five sites accredited by Ofcom. You can learn more about these sites on Ofcom's dedicated price comparison page.

Frequently Asked Questions

FAQs

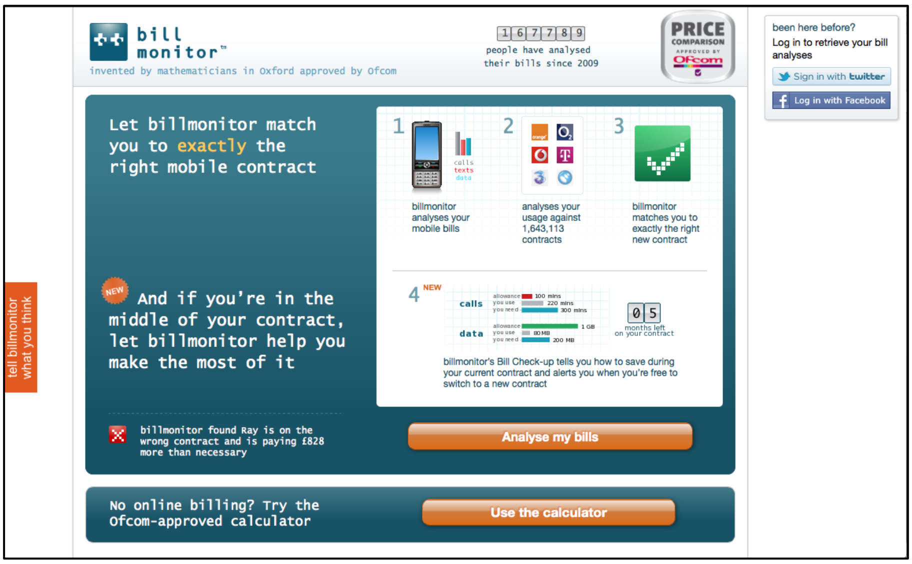
Type your question here

Select a subject | Ask

View Top Questions

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.

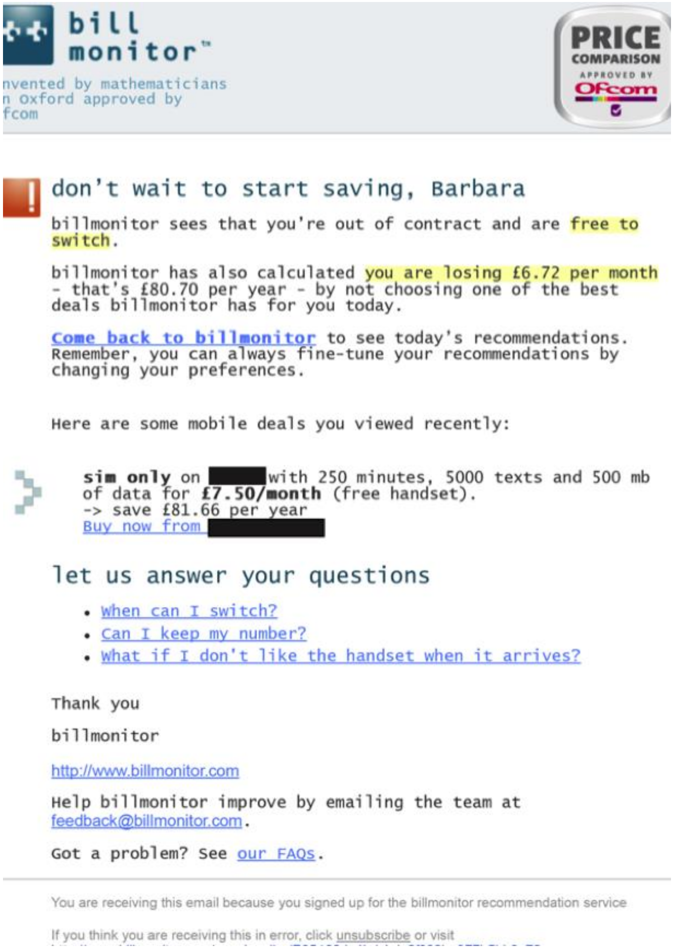
FIGURE A3: BM's ANALYSIS PAGE

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

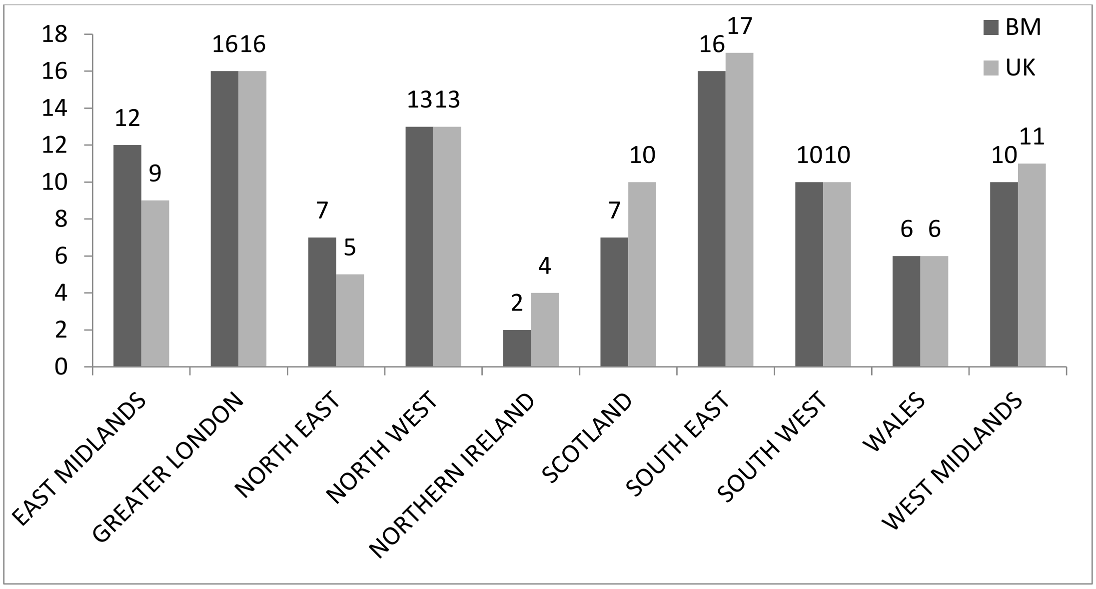


Appendix B – Representativeness of the sample and summary statistics

In this annex, we discuss the representativeness of our sample and also provide some initial statistics on savings within our sample. Note that all contracts are single-customer contracts, and we do not observe business contracts, that is, a single entity owning multiple phone contracts.

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



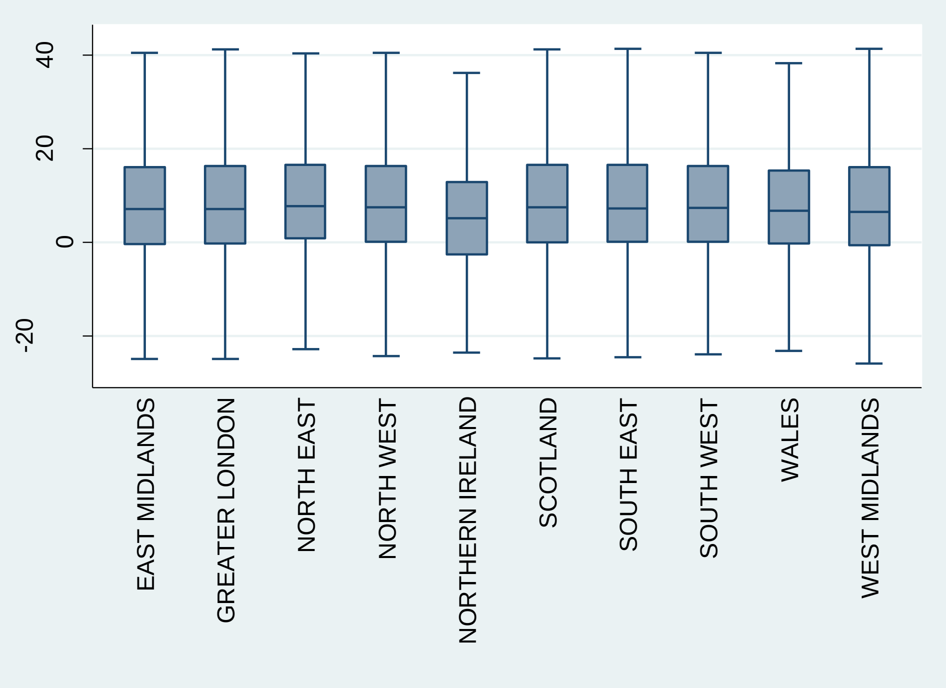
Notes: The graph above compares the percentage population distribution across regions in the UK and in the BM data.
Source: The UK population distribution based on the 2011 census, Office for National Statistics. BM population distribution based on the data provided by BM.

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), which 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

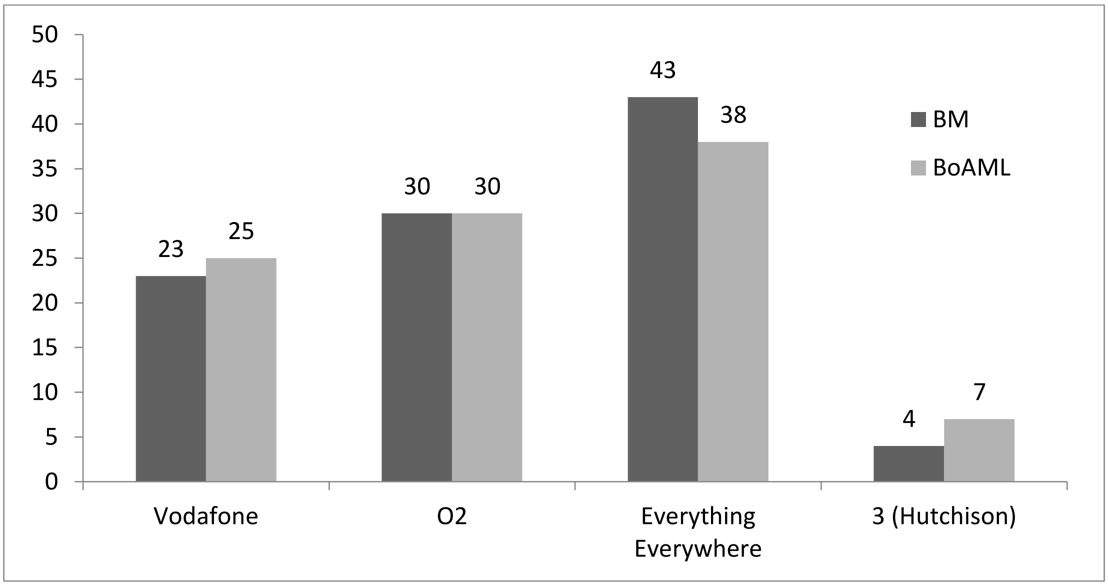
MVNOs (Mobile Virtual Network Operators) that do not have a spectrum license but rent airtime from the main licensed operators (they accounted for 8% of the total market in 2010-2012, mostly in the pre-paid segment; see Ofcom, 2013).

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.

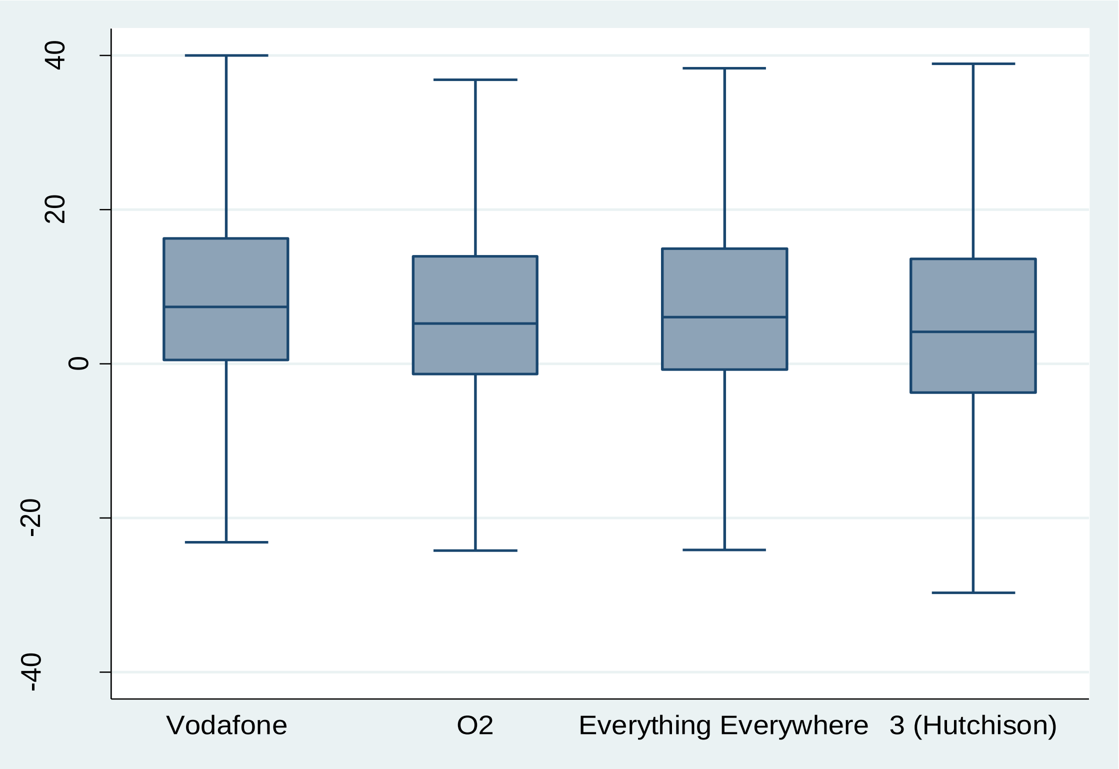
FIGURE B3: MOBILE OPERATORS' MARKET SHARES



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 illustrates, with small but significant differences among them (highest median savings for Vodafone, £7.4, and lowest for Three, £4.1).

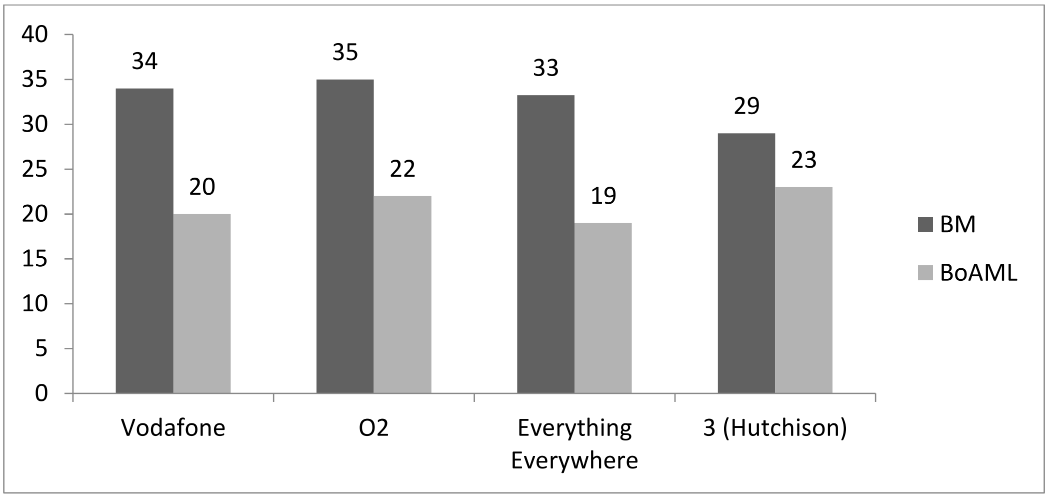
FIGURE B4: SAVINGS DISTRIBUTION ACROSS MOBILE OPERATORS



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.

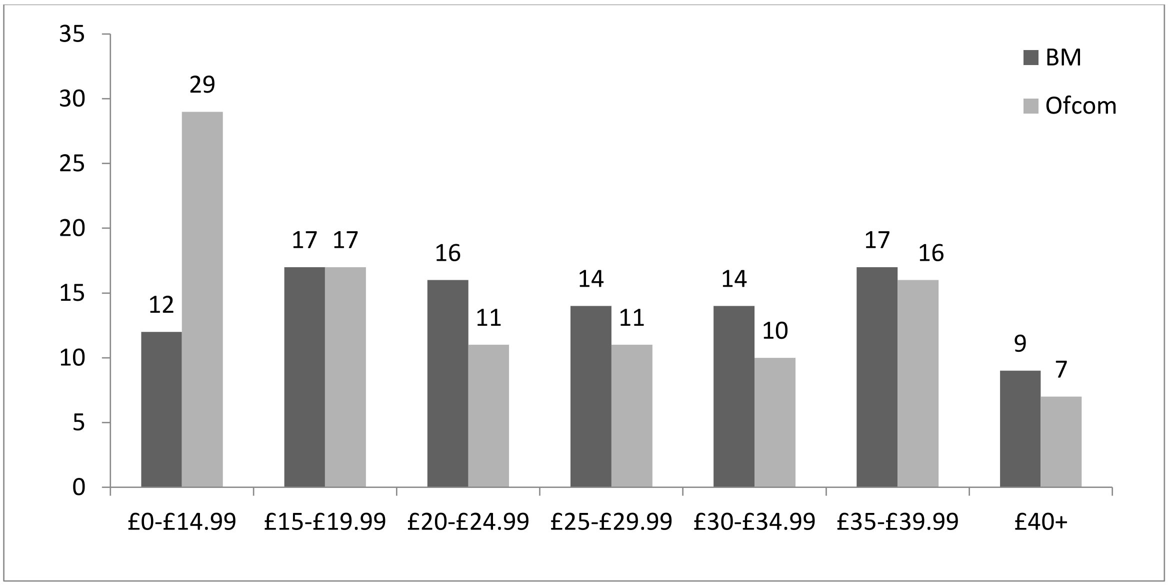
FIGURE B5: AVERAGE REVENUE PER USER ACROSS MOBILE OPERATORS



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.

Figure B6 compares the distributions of consumers belonging to different tariff plans from the Ofcom[1] 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.

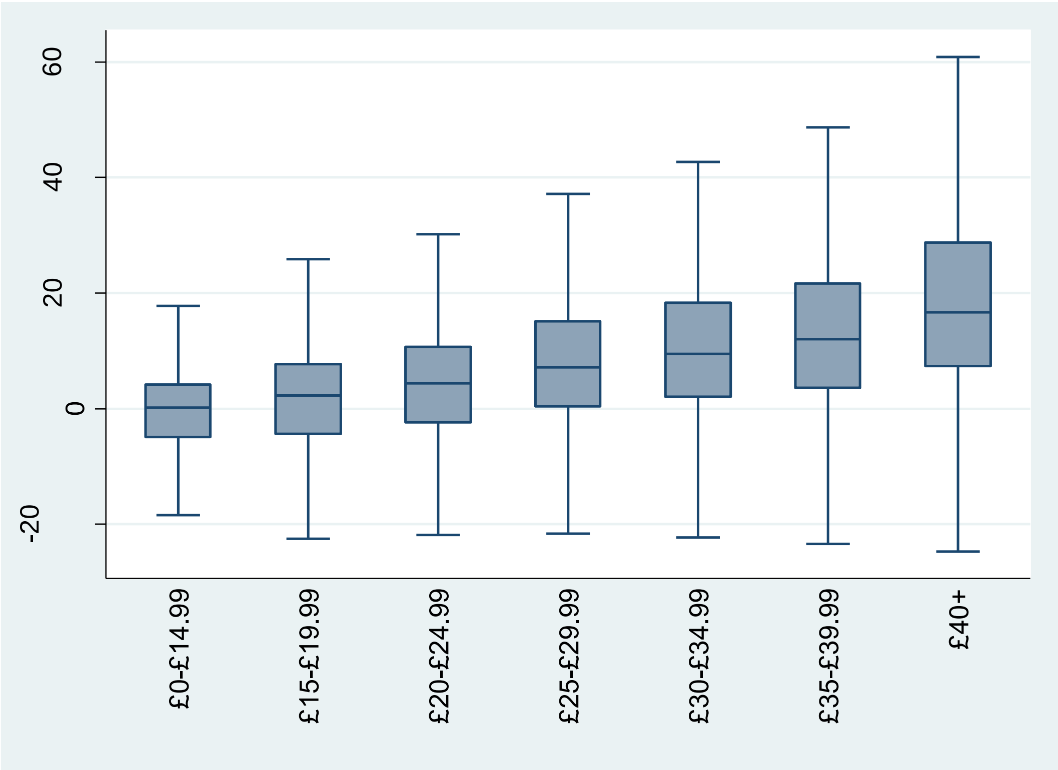
Savings can occur across any tariff category in the BM sample (see Figure B7). More savings are available to those customers choosing larger and more expensive plans.

[1] 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 closely. Because it consists only of post-paid customers, these consumers seem to consume and spend more, on average, compared to the aggregate statistics, but without 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.

Appendix C – Further robustness

In this annex, we discuss further robustness tests in relation to sample selection or measurement issues, as well as different possible interpretations of our results.

Sample selection due to attrition. Following the discussion in the main text, we also re-estimate our baseline model using information only on the first five months (which is above the median and slightly below the mean lifetime of consumers in our data) from every consumer, in order to reduce the time window within which they can deregister. Table A1, column 1 provides very similar results to those in Table 3, column 5 confirming our previous conclusions.

Sample selection due to truncation. We collected the BM data at the beginning of October of 2012. In general, our data-collection exercise is orthogonal to consumers' decision to register and use BM's services, and, as we discussed earlier, switching decisions over months do not seem to vary significantly. However, one might question whether the fact that we truncate consumers' lives at a particular point in time affects the results in any significant way. To test this hypothesis, we artificially truncate the data within our sample. Column 2 in Table A1 reports the results from our baseline specification when we truncate the data in July 2011.[2] The results for both overage and savings are statistically significant and qualitatively unchanged, indicating our timing of sampling had no significant impact on the results.

Controlling for changes in mobile operators' strategies. Given the dynamic nature of the telecommunication industry, mobile operators frequently change their tariff specifications and bundle characteristics. To control for any observed or unobserved (to us) changes in mobile operators' bundles, we re-estimate our baseline model, introducing joint operator × time FE.

[2] The date is arbitrarily chosen and corresponds to the middle of the sample; results are qualitatively robust to alternative selections.

Table A1, column 3, shows that the estimated coefficients are slightly lower (but not significantly so) and the results remain otherwise unchanged.

Previous lags for overage. Is it just last month's overage that prompts consumers to switch, or do previous lags also matter in any way? In Table A1, column 4, we re-estimate our baseline model by replacing $(overage)_{i(t-1)}$ with $(overage)_{i(t-2)}$. Its estimated coefficient is statistically insignificant.

Measurement error in savings. One could argue that if measurement error is present in calculating savings, their coefficient would be biased. Similarly, including just last month's savings may be a noisier 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, whereas the impact of overage increases slightly (Table A2).

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 unconvincing for two reasons. First, no clear a priori reason exists why consumers 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 3, column 1), the margin to adjust consumption is minimal, yet overage continues to play a significant role.

Learning. 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. Indeed, this phenomenon has been found in previous work (Narayanan et al., 2007; Miravete and Palacios-Huerta, 2014; Gopalakrishnan et al., 2015; Ater and Landsman, 2018). We also find this explanation generally plausible but not fully persuasive in explaining switching in our data. First, we study UK consumers' behavior in a mature phase of the telecoms industry. Hence, although we do not have information on their age, these customers are highly unlikely to be first-time users, unaware of their needs and consumption patterns. Second, if the learning hypothesis were true, 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, we observe consumers switching more to lower tariffs, on average (59% vs 41%), and this tendency increases as we move to lower-tariff categories.

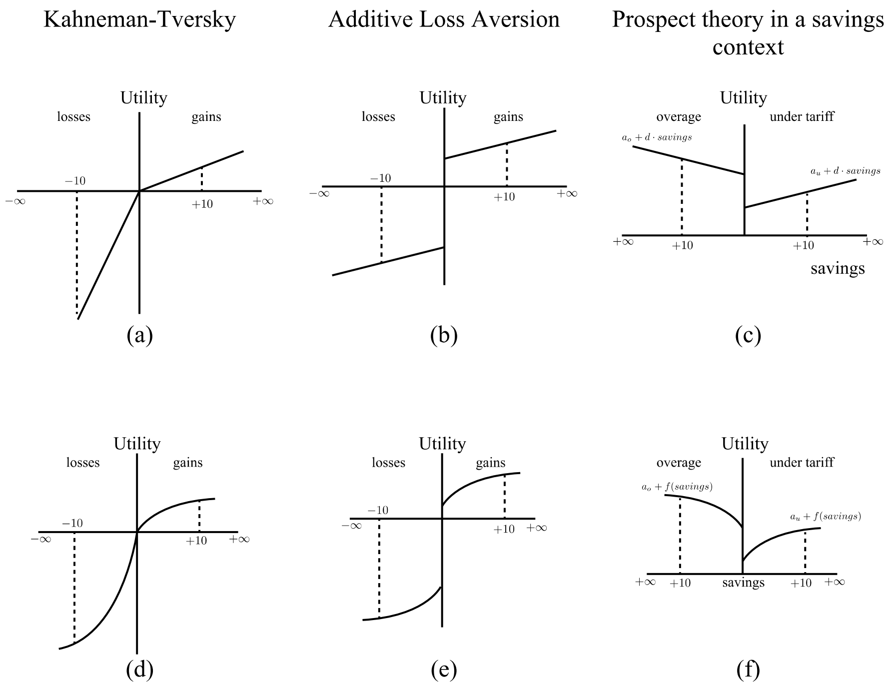
Appendix D – Prospect theory in the context of overage

Under prospect theory, the utility from a given level of savings is asymmetric, depending on whether the savings are experienced as a gain or as avoidance of a loss. Consumers who experience overage will see savings as an opportunity to avoid the loss from exceeding their tariffs. Consumers who do not exceed their allowances, will see savings as an opportunity to gain the said amount. Think of the following linear utility model for the two groups:

$$U(switching|savings) = \begin{cases} a_u + d \cdot savings, & \text{if overage} \leq 0 \\ a_o + d \cdot savings, & \text{if overage} > 0, \end{cases} \tag{D1}$$

with $a_u \leq a_o$.

FIGURE D: LOSS AVERSION IN BM's CONTEXT



We describe this utility function with the help of Figure D. The upper row of the figure gives linear forms of utility curves, whereas the lower row gives the equivalent non-linear utilities. A typical (non-linear) Prospect theory utility function as suggested by Kanheman and Tversky

(1979) is depicted in subfigure Dd. A linear approximation of this is presented in subfigure Da. Loss aversion implies that the utility function will be more distant from the horizontal axis in the domain of losses than it is in the domain of gains, meaning that a given amount of losses induces a bigger drop in utility that the same amount of gains increases utility. Kahneman and Tversky capture this increased distance of the utility function from the x-axis in the domain of losses by multiplying the utility in that domain by a factor λ > 1. Hence a typical Prospect Theory utility function would be: $U(x) = \begin{cases} v(x) \text{ if } x \geqq 0 \\ -\lambda v(-x) \text{ if } x < 0 \end{cases}$, where $v(x)$ is a standard concave utility function. The linear approximation to this would be: $U(x) = \begin{cases} \alpha x \text{ if } x \geqq 0 \\ \lambda \alpha x \text{ if } x < 0 \end{cases}$. With this specification the difference between gains and losses is captured by λ, the so-called coefficient of loss aversion. This causes the disutility of an amount x of losses to be more distant from the *x*-axes than the utility of a same amount of gains. Since in Prospect Theory $U(0) = 0$, econometrically loss aversion would be captured by a difference in the slope of x. In our setting we opt for capturing this differing distance from the x-axis through a difference in intercepts in the two domains (gains and losses). This is depicted in figures Db (for the linear case) and De (for non-linear utilities). This approach allows for a clearer identification of loss aversion through shifts in the intercept and has been used empirically by other authors to capture loss aversion with field data (e.g., Pope and Schweitzer, 2011). In this case

$$U(switching|x) = \begin{cases} a + d \cdot x, \text{ if } x \geqq 0 \\ -b + d \cdot x, \text{ if } x < 0 \end{cases}, \text{where } |a| < |b| \quad \text{(D2)}$$

Note that in our setting the loss domain is indicated by existence of overage. Hence, the same amount x of savings is experienced as potential gain if the customer is below her tariff and as avoidance of potential loss if she has overage. Hence (D2) becomes:

$$U(switching|savings) = \begin{cases} a_u + d \cdot savings, \text{ if overage} = 0 \\ a_O + d \cdot savings, \text{ if overage} > 0 \end{cases} \quad \text{(D3)}$$

Where a_i depicts the intercepts from the regression of switching on savings for the two groups (overage and no overage). This is depicted in figure Dc (Df for the non-linear case). The difference of the propensity to switch between the two groups is captured by the difference in the intercepts $(a_u - a_o)$.

In addition, prospect theory provides us with a further testable implication. According to Kahneman and Tversky's (1979) utility, presented in Figure Dd, consumers would exhibit risk aversion in gains and risk-loving attitude in losses. This feature of diminishing sensitivity both in gains and losses can be captured by the convexity/concavity of the utility function presented in Figure Dd, which in our case corresponds to Figure Df, because loss aversion is again captured by the intercept. Therefore, we also estimate a more general nonlinear model that allows us to test for the consumers' risk attitude:

$$U(switching|savings) = \begin{cases} a_u + f(savings), & \text{if overage} \leq 0 \\ a_o + f(savings), & \text{if overage} > 0. \end{cases} \quad \text{(D4)}$$

which corresponds to equation (2b) in our main text.

TABLE A1 - WHAT AFFECTS SWITCHING BEHAVIOR? - FURTHER ROBUSTNESS

	(1)	(2)	(3)	(4)
Estimation method	FE	FE	FE	FE
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$
Description	First five months only	Truncated in July 2011	Operator × Time FE	Previous overage lag
Overage$_{i\,(t-1)}$	0.026***	0.013**	0.015***	
	(0.004)	(0.005)	(0.003)	
Savings$_{i\,(t-1)}$ (x 10^3)	1.753***	0.342***	1.453***	0.202***
	(0.272)	(0.124)	(0.146)	(0.049)
Overage$_{i\,(t-2)}$				-0.003
				(0.002)
Observations	71,068	35,879	132,361	109,517
Year-Month FE	yes	yes	yes	yes
Consumer FE	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%.

TABLE A2 - ROBUSTNESS - MOVING AVERAGE MEASURE OF SAVINGS

	(1)	(2)	(3)	(4)	(5)
Estimation method	OLS	FE	FE	Logit (Odds ratio)	Proportional Hazard (Hazard ratio)
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$	pr(switching)$_{it}$
Overage$_{i\ (t-1)}$			0.017***	1.120***	1.148***
			(0.003)	(0.038)	(0.038)
Savings$_{i\ (t-1)}$ (x 10^3)	0.554***	0.551***	0.547***	1.010***	1.007***
three month lagged moving average	(0.103)	(0.155)	(0.154)	(0.001)	(0.001)
Observations	79,094	79,094	79,094	79,094	79,094
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.

TABLE A3 - SWITCHING AND RISK ATTITUDE - ROBUSTNESS

	(1)	(2)
Estimation method	FE	FE
Dependent variable	pr(switching)$_{it}$	pr(switching)$_{it}$
Overage$_{i\,(t-1)}$	0.013***	0.028***
	(0.003)	(0.004)
D2_Savings$_{i\,(t-1)}$	0.029***	0.033***
Dummy =1 if lagged savings between £5-£10	(0.003)	(0.005)
D3_Savings$_{i\,(t-1)}$	0.048***	0.065***
Dummy =1 if lagged savings between £10-£15	(0.004)	(0.006)
D4_Savings$_{i\,(t-1)}$	0.066***	0.086***
Dummy =1 if lagged savings between £15-£20	(0.004)	(0.007)
D5_Savings$_{i\,(t-1)}$	0.086***	0.111***
Dummy =1 if lagged savings between £20-£25	(0.005)	(0.008)
D6_Savings$_{i\,(t-1)}$	0.099***	0.113***
Dummy =1 if lagged savings greater than £25	(0.005)	(0.009)
Overage$_{i\,(t-1)}$ × D2_Savings$_{i\,(t-1)}$		-0.008
		(0.005)
Overage$_{i\,(t-1)}$ × D3_Savings$_{i\,(t-1)}$		-0.027***
		(0.006)
Overage$_{i\,(t-1)}$ × D4_Savings$_{i\,(t-1)}$		-0.029***
		(0.007)
Overage$_{i\,(t-1)}$ × D5_Savings$_{i\,(t-1)}$		-0.035***
		(0.009)
Overage$_{i\,(t-1)}$ × D6_Savings$_{i\,(t-1)}$		-0.021**
		(0.009)
Observations	134,276	134,276
Year-Month FE	yes	yes
Consumer FE	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.

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