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Personalized pricing for customer retention: Theory and evidence from mobile communication

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ABSTRACT

This paper analyzes firms' strategies that aim at retaining customers and examines consumers' characteristics that make them ideal targets for companies' loyalty programs. Our contribution is both theoretical and empirical. On the theoretical side, we develop a formal economic model to study the incentives of firms to offer personalized pricing plans, when consumers are at risk of leaving and are heterogeneous in service usage. On the empirical side, relying on an original dataset of customers of one of the top mobile network operators in the Italian market, we find evidence of an inverted-U relationship between the usage intensity and the probability of being the target of a personalized offer, which is consistent with the theoretical prediction. In addition, we find that anti-churn campaigns have a positive effect on customer retention.

1. Introduction

Customer retention is one of the most important concerns for firms in search of competitive advantage in mature sectors, such as the telecom industry (Kim, Park, & Jeong, 2004; Kim & Yoon, 2004; Uner, Guven, & Cavusgil, 2020). The growing availability of information and the possibility of comparing prices across different telecom operators, while increasing complexity, could in principle make it easier for customers to change provider and make it hard for companies to find appropriate strategies to reduce the churn rate (Lejeune, 2001; Uner et al., 2020, p. 101901). Despite the substantial effort in developing customer loyalty programs and ad-hoc offerings for existing customers, the churn rate in the telecom industry is still significant: in the US, it was 21% in 2018,[1] while in Europe it was around 25% for pre-paid customers and 15% for post-paid customers in 2016.[2]

Customer churn occurs mostly because customers are dissatisfied with their provider service attributes, such as call quality and prices (Czajkowski & Sobolewski, 2016; Keaveney, 1995; Keramati & Ardabili, 2011; Kim et al., 2004; Uner et al., 2020), with competing firms trying to steal customers by offering special discounts and other incentives to switch (Fudenberg & Tirole, 2000). However, telecom operators invest in different mechanisms to maintain loyalty, such as free phones, upgrades, free minutes and lock-in to the handset (Eshghi, Haughton, & Topi, 2007), so that the process of customer poaching is hindered by different types of

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[1] Customer churn rate in the United States in 2018, by industry. Retrieved October 22, 2019, from https://www.statista.com/statistics/816735/customer-churn-rate-by-industry-us/.

[2] https://tefficient.com/2016-was-a-great-year-for-mobile-customer-loyalty/.

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endogenous switching costs (Ahn, Han, & Lee, 2006; Corrocher & Zirulia, 2010; Czajkowski & Sobolewski, 2016; Farrell & Shapiro, 1998; Gerpott, Thomas, & Hoffmann, 2008; Grzybowski, 2008; Lee, Kim, Lee, & Park, 2006). One way of strengthening customer loyalty for companies is to propose personalized pricing (Richards, Liaukonyte, & Streletskaya, 2016; Wong, 2010), which enhances retention because it allows companies to reduce the uncertainty concerning what is consumed and charged (Genakos, Roumanias, & Valetti, 2015).

Among the behavioural predictors of churn, the service usage is often indicated as one of the most relevant (Lunn, 2013; Madden, Savage, & Coble-Neal, 1999; Mozer, Wolniewicz, Grimes, Johnson, & Kaushansky, 2000). However, the evidence on the existence of a monotonic relationship between customers' (monthly) expenditures and churn remains inconclusive (Ahn et al., 2006; Kim & Yoon, 2004; Madden et al., 1999; Mozer et al., 2000; Seo, Ranganathan, & Babad, 2008). On the one hand, light users are less valuable, so that firms do not have incentives to reduce the price they pay to retain them. On the other hand, high-spending users may have a lower propensity to switch because they are less informed about the alternative plans offered by other firms, which may occur if larger expenditures are driven by higher income that entails softer budget constraints and larger search costs (Mehta, Rajiv, & Srinivasan, 2003; Urbany, Dickson, & Kalapurakal, 1996).

Starting from these considerations, this paper investigates firms' personalized pricing strategies that aim at retaining customers and examines consumers' characteristics that make them ideal targets for companies' loyalty programs. Our contribution is both theoretical and empirical. On the theory side, we develop a model in which firms can offer a personalized price discount to their customers. In particular, we focus on an industry in which the Gaining Provider Led process applies, such as the Italian mobile communication industry, where the current firm is not informed about the consumer intention to switch until the contract is signed. In this case, firms can only predict which customers are at higher risk of leaving, and offer targeted promotional offers if it is profitable to so. A consumer type is two-dimensional, consisting of a surplus shifter and the switching cost. The former is observed by the firm serving a consumer and can be used to make retention offers; the latter is private information of the consumer. The model accommodates the idea of an inverted-U (thus, non-monotonic) relationship between usage intensity and the probability of being the target of a personalized offer, depending on the intensity of the two forces discussed above that are embedded in the model.

Our main contribution is empirical. In this respect, the paper uses an original dataset of one of the top mobile network operators in Italy. The data concern different types of customers: people who have and people who have not been the target of a promotion, and people who left or stayed with the company. Consistently with the theoretical model, we find an inverted U-shape between average monthly expenditure and the probability to be targeted, controlling for individual characteristics and the current tariff plan. Also, we find that anti-churn campaigns are rather effective in our sample, and consumers end up spending less after being targeted, which is expected, since they are offered more convenient contracts.

The paper is structured as follows. Section 2 provides a review of the literature on customer churn and the implementation of loyalty programs. Section 3 presents a formal model and derives its main predictions. Section 4 describes first the data, to move then to the results of the empirical analysis. Finally, section 5 concludes and provides managerial and policy implications.

2. Customer churn and strategies for customer retention: a literature review

2.1. *The determinants of customer churn and the role of switching costs*

Customer defection or churn is the decision to terminate a contract with a particular company (Chandar, Laha, & Krishna, 2006; Stewart, 1998). In the telecom industry, even if companies attempt to strengthen their customer base while acquiring new clients, the number of churning customers grows as the market becomes more mature, since more information is available and accessible to the customers and competition becomes more intense. The increase in customer churn causes a decrease in profit level, and consequently, makes a company lose a privileged position in the market (Ascarza et al., 2018; Gerpott, Rams, & Schindler, 2001; Glady, Baesens, & Croux, 2009; Reichheld & Sasser, 1990).

The literature has largely looked at the determinants of customer churn (Ahn et al., 2006; Chakravarty, Feinberg, & Rhee, 2004; Eshghi et al., 2007; Gerpott et al., 2001; Keaveney, 1995; Keramati & Ardabili, 2011; Kim & Yoon, 2004; Seo et al., 2008; Uner et al., 2020, p. 101901) and has identified two main sets of factors in the telecom sector: the features of the service (e.g. call quality, price, contract duration) and the individual characteristics (socio-demographics, usage intensity, monthly expenditure).

First, the retention of customers depends on the level of satisfaction with the specific service attributes such as call (network) quality, tariff/price level, handset characteristics and brand image (Calvo-Porral & Lévy-Mangin, 2015; Gerpott et al., 2001; Kim & Yoon, 2004; Lee et al., 2006; Uner et al., 2020, p. 101901). Dissatisfaction indicators such as the number of complaints and the call drop rate have a significant impact on the probability of churning (Ahn et al., 2006). Conversely, a complex service plan, a sophisticated handset, membership card programs, long-term contracts and a high quality of service are positively related to customer retention (Seo et al., 2008).

Concerning the second set of factors, service usage is often indicated as one of the most relevant behavioural predictors of churn (Lunn, 2013; Madden et al., 1999; Mozer et al., 2000). The literature has provided some evidence on the fact that heavy spenders are more likely to churn (Ahn et al., 2006; Eshghi et al., 2007; Seo et al., 2008): customers who spend more are more price-sensitive and tend to explore different services. However, the results are not conclusive and some works do not find a significant relationship between the spending levels and the probability of churning when controlling for customer satisfaction indicators (Kim & Yoon, 2004), or even find that the amount of services used by the customers reduces customer churn (Keramati & Ardabili, 2011). We do contribute to this literature by investigating specifically the role of service usage in stimulating companies' personalized offers to customers to avoid the churn.

Customer satisfaction affects customer loyalty and customer retention, but customers may decide to stay with their operator even in case of low satisfaction, due to the presence of switching costs (Chuang, 2011; Gerpott et al., 2001; Kim et al., 2004; Lee et al., 2006), i. e. the effort and expense customers face when switching from one product to another (Klemperer, 1995). Switching costs may refer to the product/service level or to the company level, i.e. they may be embedded into the product used – because of the technical specificities of the product – or may be the results of companies' strategies and contract design, and there is evidence that they are still significant in the mobile telecom industry (Buehler, Dewenter, & Haucap, 2006; Czajkowski & Sobolewski, 2016; Grzybowski & Pereira, 2011; Lunn, 2013). For example, consumers might have to communicate their habitual contacts that they have changed operator since this change affects the cost of calls for those who call them in presence of on-net price discrimination.[3] Furthermore, operators can force consumers to use the handsets exclusively within their network, and unlocking comes at a cost. Finally, there are search costs because consumers have to gather information about other operators' tariff plans (Ahn et al., 2006; Corrocher & Zirulia, 2010; Farrell & Shapiro, 1998; Gerpott et al., 2008; Grzybowski, 2008; Lee et al., 2006; Lunn, 2013).

2.2. Retention strategies and behavior-based price discrimination in competitive markets

There exist two basic approaches to manage customer churn. Untargeted approaches rely on mass advertising to increase brand loyalty and retain customers, while targeted approaches rely on identifying customers who are likely to churn, and then either provide them with a direct incentive (e.g. a rebate), or customize a service plan to make them stay (Coussement & Van den Poel, 2008; Neslin, Gupta, Kamakura, Junxiang, & Mason, 2006). This second type of approaches involves the segmentation of customers, the computation of their churn probabilities and the development of complex churn-prediction tools (Ascarza, 2018; Hung, Yen, & Wang, 2006).

Targeted approaches are adopted by firms willing to retain their customers and by firms trying to induce switching from competitors. These are examples of behaviour-based price discrimination (Armstrong & Huck, 2010; De Nijs, 2017; Fudenberg & Tirole, 2000; Richards et al., 2016; Villas-Boas, 1999), whereby firms discriminate prices across different customers based on the observation of individual characteristics and past service usage patterns or purchasing behaviour. Consumers may perceive the products as perfect substitutes initially, but switching costs arise if they change supplier (Chen, 1997; Taylor, 2003). Furthermore, consumers may have an exogenous brand-related preference for a firm, which may be disclosed by purchase history (Fudenberg & Tirole, 2000; Villas-Boas, 1999).

In the words of the Office of Fair Trade (OFT), personalized pricing is: "… *the practice where businesses may use information that is observed, volunteered, inferred, or collected about individuals' conduct or characteristics, to set different prices to different consumers (whether on an individual or group basis), based on what the business thinks they are willing to pay." (OFT, 2013*, p. 3*, p.3)*. While this type of discrimination has been for long very common in many service industries (retailing, telecommunications, banking and airlines), the emergence of granular price management algorithms, advanced data analytics and shopping apps have caused a widespread diffusion of personalized pricing for consumer products and services (OECD, 2018; Weisstein, Monroe, & Kukar-Kinney, 2013). Personalized prices are developed based on the estimation of customers' willingness to pay, but also on the value a customer has for a firm. For this reason, firms can set lower prices to reduce the risk of losing consumers: this means that the price-setting mechanism is affected by the probability of customers' churn.

In general, firms should offer lower prices to their competitors' customers to give them incentives to switch, and higher prices to their customers to capture surplus from them (Caillaud & De Nijs, 2014; Uner et al., 2020, p. 101901). However, while behaviour-based price discrimination is unambiguously profitable if adopted by a single firm, industry profits can fall, if all firms practice it. Thus, from a policy perspective, banning behaviour-based price discrimination has an ambiguous effect on the overall welfare, also considering the impact of such a strategy when firms fix their prices in an initial stage, before customer recognition is possible (Esteves, 2010).

In the next section, we develop a formal model with the aim of understanding which customers are the ideal target for firms' retention promotions. Retention offers within a model of behaviour-based price discrimination have been considered in Esteves (2014). In this paper, a two-stage model is developed in which, in the second period, firms can offer a price discount to their customers who signal the intention to switch to a competitor. Therefore, the model aims to represent the so-called Losing Provider Led processes, in which the consumer willing to switch has to contact her existing provider first. For UK mobile phone services, for instance, consumers must ask their current operators for a Porting Authorization Code to secure number portability. The main result of the paper concerns the welfare implications of behaviour-based price discrimination with retention offers: it is shown that such a pricing strategy is beneficial for consumers and the overall surplus, but detrimental to the industry profits. Our model differs from the one in Esteves (2014) in several dimensions. First, we focus on industries in which Gaining Provider Led process applies, such as the Italian mobile communication industry, where the current firm is not informed about the consumer intention to switch until the contract is signed. Second, consumers in our model are heterogenous in usage intensity, which is used by the firm to predict the churn risk, while in Esteves (2014) consumers have a brand (horizontal) preference, which may be disclosed after the first period. Third, our model is static, considering a "second period" in which the firm has already an installed base, while Esteves fully characterizes the first-period prices, when retention strategies are allowed.

[3] Contracts can be designed so that on-net tariffs (i.e. tariffs for consumers served by the same operator) are lower than off-net tariffs (i.e. tariffs for consumers served by different operators).

3. Personalized pricing for customer retention: a formal model

3.1. Model description

Let us consider a mature telecom market in which a firm (say firm *i*) offers a product (the telecom service) at zero marginal cost. Firm *i* has an installed base of consumers, to which it offers a tariff plan consisting in a single (linear) price $\overline{p}$, Each consumer *k*, attached to firm *i*, is identified by a type $\theta_k \in \left[\underline{\theta};\overline{\theta}\right]$. Consumers' type θ is a parameter in the utility function, which is given by $U(x,y;\theta)$, where x is the consumption of the telecom service, and y is a numeraire good. We will use a specific utility function as follows:

$$U(x,y;\theta) = x - \frac{x^2}{2\theta} + y \tag{1}$$

Given the budget constraint $px + y = I$ (where I is income), a linear demand function is easily derived as:

$$x(p;\theta) = \theta(1-p) \tag{2}$$

For a given price p, the consumer net surplus is $\frac{\theta}{2}(1-p)^2$. It follows that θ acts as a demand, expenditure and surplus shifter. We shall assume that firms can perfectly observe θ in their installed base (while other firms cannot). In addition, given (2), $\frac{1}{2}$ is the monopoly price for any θ, so that we restrict our attention to $\overline{p} < \frac{1}{2}$.

Since we are interested in retention pricing strategies, we rule out the possibility that firms can change the tariff plan available to all their existing consumers (i.e. $\overline{p}$). Instead, firm *i* can offer $\widehat{p}_\theta$, i.e. the personalized tariff plan contingent to the type θ.[4] We will refer to such a plan also as the customer retention offers. We shall assume that firms cannot impose a personalized tariff plan to a specific consumer, so that the personalized offer will be accepted only if $\widehat{p}_\theta \le \overline{p}$. At the same time, the other firms in the market can propose a tariff plan targeted to the customers of firm *i*. We will refer to such a plan as the poaching offer. If there are at least three firms in the market and firms do not incur any fixed cost in attracting a new customer and serving her, Bertrand competition for firm *i*'scustomers will drive the poaching offer down to marginal cost, i.e. to zero. Assuming that the products in the market are homogenous, the consumer net surplus (gross of the switching cost) of firm *i*'s customers who change operator will be then given by $\frac{\theta}{2}$.

We make two key assumptions concerning customers *switching behavior*. In particular, $\alpha(\theta)$ is the probability that a consumer of type θ can actually observe the other firms' poaching offers. We will define such consumers as *aware*. In addition, for aware consumers, changing firm entails a switching cost σ. Firms do not observe the switching cost, but know its distribution, which is uniform over the unit interval.

Switching occurs if the net surplus that a consumer can obtain by the new operator minus the switching cost is greater that net surplus that the consumer can obtain from her current firm. Then, for a generic price $p$the probability of switching is given by [5]:

$$\Pr\left(\frac{\theta}{2} - \sigma > \frac{\theta}{2}(1-p)^2\right) = \Pr\left(\sigma < \frac{\theta}{2} - \frac{\theta}{2}(1-p)^2\right) = \frac{\theta}{2}\left[1-(1-p)^2\right] = \frac{\theta}{2}p(2-p) \tag{3}$$

from which we see that such probability is increasing both in θ and p.

It follows that, again for a generic price p, the expected profit conditional on type θ is given by:

$$E\Pi = [1-\alpha(\theta)]\theta(1-p)p + \alpha(\theta)\theta(1-p)p\left[1 - \frac{\theta}{2}p(2-p)\right] \tag{4}$$

The first term is the profit from unaware consumers (who never switch), while the second term is the expected profit from aware consumers, where $1 - \frac{\theta}{2}p(2-p)$ is the probability of retention. (4) can be simplified to:

$$E\Pi = \theta(1-p)p - \alpha(\theta)\frac{\theta^2}{2}(1-p)p^2(2-p) \tag{5}$$

which makes it clear the negative impact that the risk of switching can generate on profits.

The behavior of $\alpha(\theta)$ plays a key role in the model. In particular, we shall assume that $\alpha'(\theta) \le 0$ and $\alpha''(\theta) < 0$, with $\alpha\left(\underline{\theta}\right) = 1$ and $\alpha'(\underline{\theta}) = 0$.[6] In words, the fraction of aware consumers is supposed to be lower for high-spending customers than for low-spending consumers. High-spending consumers may be less *informed* about alternative plans offered by competing firms, if larger expenditures are associated with higher income and higher income to softer budget constraints and larger search costs.[7] For instance, Urbany et al. (1996) find that income has a significant negative impact on price search effort in a sample of US consumers, while Mehta et al.

[4] As a matter of fact, the firm implements group pricing, if there is a group of consumers sharing the same θ.

[5] We shall assume that θ is such that the probability of switching is well defined.

[6] The assumption on $\alpha''(\theta)$ can be relaxed as long as $\alpha''(\theta) <$ - $2\alpha'(\theta)$ for sufficiently low values of θ, i.e. if low types are sufficiently informed.

[7] In our context, the consumer type has also an impact on the search benefit side, with high-spending users having higher benefits together with higher costs. The overall effect is thus theoretically ambiguous. However, while the estimate of cost is ex-ante relatively easy, consumers may have biased expectations of search benefits and, in particular, they can underestimate the saving from alternative tariff plans. Kling et al. (2012) show that this is the case in the market for Medicare prescription drugs in the US.

(2003) identify a positive relationship between per capita income and search costs, using scanner data for liquid detergents.[8]

3.2. Results

We are now in the position to state our main result, summarized in Proposition 1 (the Proof is in Appendix A).

Proposition 1. Consumers with an intermediate value of θ $\left(\widehat{\theta}_L < \theta < \widehat{\theta}_H\text{, where } \underline{\theta} \leq \widehat{\theta}_L < \widehat{\theta}_H \leq \overline{\theta}\right)$ will receive a retention offer.

In words, Proposition 1 says that, in general, retention offers are made to consumers whose type is neither too low, nor not too high. First of all, it is important to remember that, even if a personalized (type-specific) offer would be always profit-enhancing, firms cannot impose a tariff above the current tariff plan. As a consequence, the consumers who are the target of the retention offers are those for which the optimal personalized price is below the current price. Having said that, the intuition behind Proposition 1 is as follows. On the one hand, low type consumers are not made an offer because they have a low value for the firm, if retained. On the other hand, high type consumers, although valuable, are less likely to be aware consumers, and so the firm making them an offer runs the risk of targeting high-spending consumers that would not switch anyway. Thus, the firm targets the segment $(\widehat{\theta}_L, \widehat{\theta}_H)$, i.e. the valuable and aware consumers. Nevertheless, Proposition 1 does not exclude the possibility of "corner solutions", in which $\widehat{\theta}_L = \underline{\theta}$ or $\widehat{\theta}_H = \overline{\theta}$. When $\widehat{\theta}_L = \underline{\theta}$, retention offers are made to all types below a threshold $\widehat{\theta}_H$; when $\widehat{\theta}_H = \overline{\theta}$, retention offers are made to all types above a threshold $\widehat{\theta}_L$.[9] Fig. 1 represents graphically the set of targeted consumers, by depicting the optimal personalized price and the current tariff plan when both thresholds $\widehat{\theta}_L$and $\widehat{\theta}_H$ strictly lie between $\underline{\theta}$ and $\overline{\theta}$. [10]

Proposition 1 is brought to the data in Section 4. In general, we expect an inverted-U relation between consumers' expenditure, as proxy of consumer type θ, and the probability to receive a retention offer, which corresponds to the case in which the interval $(\widehat{\theta}_L, \widehat{\theta}_H)$lies strictly between $\underline{\theta}$ and $\overline{\theta}$. However, a priori we cannot exclude both a monotonically increasing or decreasing relationship, if only the left or right side of the inverted-U curve is observed.

Three additional observations are in order. First, the assumption of linear prices can be rightly considered as restrictive. While a full characterization of optimal nonlinear prices is outside the scope of the present paper, we conjecture that our results can be extended to nonlinear tariffs as long as the marginal impact of a price variation on consumer net surplus is stronger for the high type consumers. This property, together with a negative relationship between the consumer type and the probability of being aware, is critical for our results.[11] Empirically, for the tariff plans considered in our empirical analysis (see Table B1 in Appendix B), the condition is likely to be satisfied, especially if one considers the multiplicity of services offered (voice, Internet, MMS…).

Second, the assumption of product homogeneity can be relaxed without qualitatively affecting our results. In particular, we consider an extension of the model in which the service quality of the focal firm is perceived as lower compared to the quality of the alternative firms.[12] This can capture customer dissatisfaction with her current operator, a factor that the literature has identified as most important to explain the churn rate (see Section 2). Unsurprisingly, we find that this would lead the firm to propose retention offers to a larger set of customer types, but the relationship between customer type and the probability to receive a retention offer summarized by Proposition 1 continues to hold (and, in addition, customer dissatisfaction alone cannot generate an inverted-U relationship). Incidentally, we also note how the profitability of retention offers, notwithstanding product homogeneity, comes from the fact that we deviate from perfectly competitive markets in two dimensions, i.e. by assuming the existence of switching costs and unaware consumers.

Third, while endogenizing $\overline{p}$ would be theoretically appealing and in line with the dynamic focus of most of the existing literature on behaviour-based price discrimination, per se it would not add too much to the development of a framework for the empirical analysis, in which the customer current tariff plan is used as a control variable. However, there is a property of $\overline{p}$ which is important for our predictions, i.e. that $\overline{p}$ can lie in principle strictly between 0 (the marginal cost) and ½ (the monopoly price). In fact, for $\overline{p} = 0$, no consumer will receive an offer, while for $\overline{p} = 1/2$, all consumers will. In the Supplementary Material, we sketch a two-period model, in which firms choose $\overline{p}$ in the first stage and the profit-maximizing value $\overline{p}^*$ satisfies $0 < \overline{p}^* < 1/2$. In the model, we assume in particular that the probability of being aware in the second period is positively affected by $\overline{p}$, which captures the idea that higher prices can push

[8] In addition, a higher expenditure may be due to a lower degree of customer *sophistication*, and if lower sophistication entails also lower attention towards other firms' offers, a lower fraction of aware users will be observed among high-spending users. In that respect, a recent theoretical and empirical literature in behavioral industrial organization has been developed on the premise of boundedly rational behavior on the consumers' side (Spiegler, 2011) and a bunch of empirical papers has shown that this can be particularly the case in telecommunications markets, such as Bolle and Heimel (2005), Lambrecht and Skiera (2006), Corrocher and Zirulia (2009), Haucap and Heimeshoff (2011) and Grubb and Osborne (2015). However, it must be observed that, while lower customer sophistication can induce higher spending, tariff choices that are not apparently cost minimizing may be shown to be fully rational in a richer setting. For instance, in presence of spending uncertainty, a flat-rate plan may be superior to a more expensive pay-per-use tariff if one considers the "option value" of maintaining predictable level of spending (Kridel, Lehman, & Weisman, 1993).

[9] The first case may occur when the probability of consumer awareness decreases relatively fast as θincreases. The second case can be observed if high types have a high probability to be aware.

[10] $\widehat{p}^*_\theta$ is the solution of a third-degree polynomial equation (see the Proof of Proposition 1), whose exact value can be obtained but is too complicated to be reported here.

[11] To see formally why a $\theta -$ dependent probability of switching is crucial for our results, see the Proof of Proposition 1.

[12] See the Supplementary Material for further details.

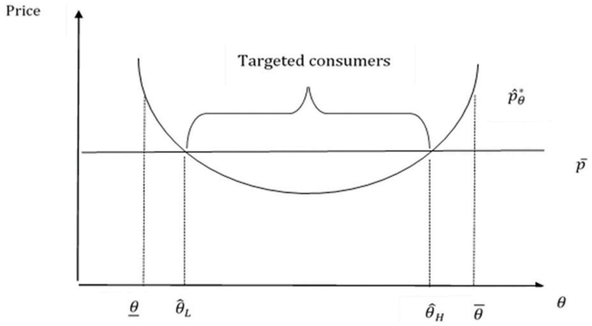

Fig. 1. Targeted consumers

consumers to search more intensively for a better deal. As a consequence, firms have the incentive to keep their initial price below the monopoly level.[13]

4. Personalized pricing for customer retention: empirical evidence from mobile communication

This section provides the main contribution of this paper, by investigating the characteristics of consumers who made them a target of anti-churn campaigns. We do so using an original dataset from one of the leaders in the Italian mobile telecom market, one of the most developed in the world (Corrocher & Zirulia, 2010). The dataset includes a random selection of pre-paid card customers, which may or may not have been targeted for churn prevention campaigns between November 2012 and March 2013. We choose to examine the prepaid card market, since it accounts for 86.2% of the total mobile users and guarantees also some variability in the monthly expenditure. Furthermore, available evidence shows that churn-rate is considerably higher for pre-paid than for post-paid customers.[14] We also show evidence on the effect of churn prevention campaigns, which is in line with our theoretical framework.

4.1. Dataset and variables' description

The dataset was built through a random sampling on the company pre-paid cards' customers in the period November 2012–March 2013. In particular, we relied on three different datasets: the first includes pre-paid card customers who were targeted with anti-churn prevention campaigns; the second includes pre-paid cards customers who were not targeted with anti-churn prevention campaigns, the third includes pre-paid card customers who left the company (irrespectively of the treatment). Based on the share of targeted customers over total customers we extracted a random sample of 17000 targeted customers (10% of the total number of targeted customers in the period) and 135004 customers who were not targeted for any campaign during the reference time. For these two groups of customers, we then recovered the information on whether they left the company or not. Both groups include zero traffic sim cards and cards which were deactivated before March 2013.

To capture the effect of the anti-churn action on customers, the targeted group is observed over three months both before and after this event. For this analysis, we only consider the three months before the anti-churn campain for this customer group. Instead, the period for non-targeted sim cards covers the reference period November 2012–March 2013. Table 1 shows the overall composition of the dataset.

We have information on whether customers are targeted or not for the *anti-churn* campaign as well as on the campaign's effect in terms of customers' *retention*. Telecommunication service providers largely rely on call patterns to identify potential churners (Wei & Chiu, 2002). On the one hand, the decision to churn is typically associated with changes in call patterns, which represent a warning signal for the company. On the other hand, mobile phone usage reflects customers' quality and it allows service providers to target valuable users. Our main predictor of interest is, therefore, customers' average monthly expenditure. Other relevant variables within the literature cover contract characteristics and customer demographics. For this study, we consider information concerning the *tariff plan*, customers' *age*, *gender* and region of *residence*. Table 2 summarizes the main variables.

[13] The reader is referred to the Supplementary Material for further details.
[14] https://inform.tmforum.org/research-reports/inspire-loyalty-customer-lifecycle-management.

Table 1
Dataset composition.

anti-churn	active		deactivated	total
	other	*zero-traffic*		
yes	15,867 (93%)	633 (4%)	500 (3%)	17,000
no	10,545 (7%)	64,855 (48%)	59,604 (44%)	135,004

Table 2
Description of the main variables.

variable	Description
retention	Binary outcome variable taking value 1 if the customer stays
anti-churn	Binary treatment variable taking value 1 if the customer was targeted by the anti-churn campaign
average monthly expenditure	Continuous variable capturing call patterns (EUR)
age	Continuous variable indicating customers' age (years)
gender	Binary variable taking value 1 if male
residence	Categorical variable indicating the region of residence in Italy (1 = North west, 2 = North east, 3 = Centre, 4 = South)
tariff plan	Categorical variable capturing 16 tariff plans

4.2. Descriptive statistics

Within our dataset, the call patterns, which in the theoretical model depend on consumer-type θ, are captured by the average monthly expenditure, which is a meaningful ground of comparison between targeted and non-targeted subjects.[15] Table 3 shows that the targeted customers are better clients, i.e. clients with a higher average monthly expenditure: this trend holds across different quartiles. The other group displays an overall lower level of monthly expenditure, but also large outliers at the top percentile, indicating that customers with either a very low or a very high spending level are not targeted.[16] This descriptive evidence is a first support to our theoretical prediction.

The other predictors of interest are demographic variables, which are likely to affect customers' quality and loyalty (Ahn et al., 2006; Gerpott et al., 2001; Kim & Yoon, 2004; Lee et al., 2006). Table 4 reports the descriptive statistics for the variable age, which is normally distributed. We can see that the central part of the distribution is more likely to be targeted. Table 5 shows the tabulation for residence: the South of the country is more represented than the other regions in both groups. Finally, 58% of the individual in our sample are males, this share decreases to 54% when considering the treated alone.

Finally, we look at the *tariff plan*, as a control for the price paid by customers.[17] Table B1 in the Appendix shows the characteristics of the 13 tariff plans of the customers in our dataset.

4.3. Which customers firms decide to treat?

We now test empirically which customers' characteristics affect the company's targeting decisions. We estimate a logit regression to test the effect of the selected predictors on the probability of a customer being targeted for the anti-churn campaign. To account for non-linear relationships between the average monthly expenditure and the log odds of the dependent variable, we log-transform the covariate and we include the square term. The regression results are reported in Table 6.

Consistently with our model, we observe that an increase in the average monthly expenditure increases the probability of a customer being targeted at a decreasing rate, as the squared term negative. The tipping point falls in correspondence of log(average monthly expenditure) = 1.88, i.e. average monthly expenditure = 6.60. This value corresponds to the 83rd percentile of the variable distribution. [18] Fig. 2 shows the predicted probabilities for each level of log(average monthly expenditure).

Considering the odds ratios, a unit increase in log(average monthly expenditure) leads to 6.36 times higher probability to be

[15] Note that targeted and non-targeted customers are not observed over the same period. To overcome this issue, a key assumption we rely on is the relatively stable conduct of the records which were not targeted for the anti-churn campaign. To verify this assumption, we compare the average monthly expenditure of the controls over the whole period vis à vis the total expenditure in March (end of the period). The Spearman rank correlation rejects the null hypothesis of independence between the two periods, signalling a stable level of expenditures. Repeating the exercise considering only sim cards that are still active at the end of the period, the outcome does not change. Detailed results are available upon request.
[16] This interpretation is also supported by the higher standard deviation reported.
[17] For targeted consumers we considered the pre-treatment tariff plan.
[18] The U-shape test proposed by Lind and Mehlum (2010) confirms the presence of an inverted U-shape between average monthly expenditure and the probability to be targeted. Following Simonsohn (2018), we ran additional tests to verify the presence of a U shape relationship by estimating two regression lines (instead of relying on the square term), one for $x \leq xc$ the other for $x \geq xc$, where xc is the tipping point. We estimated both linear and cubic splines to replace the original variable with piece-wise functions having a linear relationship with y. In both cases we find that the coefficients of the piece-wise functions are positive and significant before the tipping point, negative and significant after the tipping point; tests results are available upon request.

Table 3
Average monthly expenditure per group.

anti-churn	obs	mean	sd	min	.25	median	.75	max	p-value
yes	17,000	5.37	8.06	0.00	0.84	2.79	6.78	137.66	0.000
no	135,004	3.50	8.97	0.00	0.00	0.11	3.25	339.84	

Table 4
Age distribution per group.

anti-churn	obs	mean	Sd	min	.25	median	.75	max
Yes	17,000	48	13,5	17	38	47	56	99
No	135,000	44	14	15	33	43	53	85

Table 5
Residency tabulation (no. of customers) per group.

Residence	anti-churn	
	yes	*no*
north west	4103	34,035
north east	4069	29,111
Centre	3934	31,520
South	4894	40,334
Total	152,000	100

Table 6
Logit regression testing the determinants of treatment.

DV = anti-churn	coef.	std. err.	[95% conf. interval]	
log(average monthly expenditure)	1.85***	0.03	1.80	1.91
log(average monthly expenditure)ˆ2	−0.49***	0.01	−0.51	−0.47
Age	0.01***	0.00	0.01	0.01
Gender	−0.18***	0.02	−0.22	−0.15
Residency				
north-west	−0.094***	0.025	−0.143	−0.045
north-east	−0.024	0.025	−0.074	0.025
South	0.056*	0.024	0.008	0.104
tariff plan	Yes			
Constant	−2.30***	0.06	−2.42	−2.18
Observations	151,345			
Rˆ2	0.13			

Note: p-value<0.05*, <0.01**, <0.001***.

treated, while a unit increase in the square term decreases the probability to be treated by 40%.[19] This finding supports Proposition 1 in the theoretical model in so far retention offers are made to consumers with neither too low nor too high spending levels: the firm is less likely to make an offer to low-value customers, even if at risk of leaving (i.e. low spending consumers) and to consumers who, although valuable, are less likely to be aware of alternatives, and so less mobile.

As for the control variables, we expect them to affect the probability for a consumer to be targeted as long as they directly influence the level of switching costs and the degree of awareness. It turns out that a unitary increase in age increases the odds of being targeted by 1%. We also observe that for a male, the odds to be treated are 20% lower than for a female. Lastly, considering customers whose residency is in the central regions as a reference, we note that the south of the country is more likely to be targeted than the northern regions. As a robustness check, we repeated the same regression using a probit model. The results are consistent (see Appendix C).

[19] Odds ratios are calculated as exp(log odds). The coefficient of log(average monthly expenditure) in log odds is log(6.36). A 1% increase in average monthly expenditure is equivalent to an increase of log(1.01) in log(x). So the coefficient changes by log(6.39)*log(1.01). In odds ratio this change is exp[log(6.39)*log(1.01)] = 1.0186266 = 1.02. Therefore, if the average monthly expenditure increases by 1%, the odds for a customer to be treated increase by 2%.

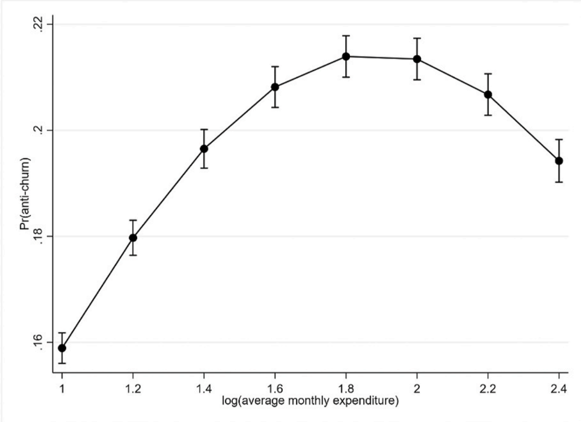

Fig. 2. Predicted probabilities with 95% CIs.

4.4. The effect of the anti-churn campaigns

As we anticipated, a limitation of our data is that we do not have information about the characteristics of the retention offers and we do not know whether targeted consumers accept them or not. Our theoretical framework is based on the premise that firms design their retention offers tailoring them on consumers' observable characteristics, and so we expect them to rather effective in their purpose. However, to be accepted, such offers should be more convenient for users compared to their current plan, leading to lower expenditures if they are accepted. In this section, we show evidence in line with these theoretical arguments.

As for the first point, we assess the impact of the anti-churn campaigns on consumers' retention. Notably, this type of treatment effect exercise suffers from the "fundamental problem of causal inference" whereby we can observe only one outcome per each individual (Holland, 1986). Moreover, the non-random nature of the treatment assignment implies that large differences in covariates may exist, thus making a direct comparison of outcomes between treated and controls misleading (D'Agostino, 1998). To reduce the bias in the estimation of the treatment effect, we adopt a matching technique, broadly defined as a method which aims to 'balance' the distribution of covariates which are known to be related to the treatment assignment and the outcome across the two groups (Rosenbaum, 1999). We seek to match cases based on the pre-treatment values of the variables affected by the anti-churn action in addition to age, gender and residency. As most non-experimental study methods, the validity of a matching built on observable covariates assumes ignorability, i.e. there are no unobserved differences between the two groups, conditional on the observed covariates (Rubin & Thomas, 2000). In this respect, it is worth noting that matching on the observed covariates controls for the unobserved covariates, in so much as they are correlated (Stuart, 2010).

To measure the degree of similarity between individual *i* and *j* on the selected covariates, we adopt the Nearest Neighbour Matching estimator (Abadie & Imbens, 2006; Rubin, 1973), which is a non-parametric estimator assigning the control case *j* with the shortest distance *Dij* to treated individual *i,* with replacement[20]. The distance *Dij* is defined using Mahalanobis distance on continuous variables, namely log(average monthly expenditure) and age. Instead, we impose exact matching on factor variables gender, residency and tariff plan.

We estimate both the average effect of the treatment on the treated (ATET) and the average treatment effect (ATE). The former refers to the average effect of the anti-churn campaign on the decision to stay or leave of the treated – i.e. the main performance indicator of the provider's action. The latter reports the estimated effect of the campaign on all individuals.[21] Table 7 shows that in both cases, the anti-churn campaign has a positive and significant effect on the customers' decision to stay. At the population level, the campaign would have increased the probability of a customer to stay by 39%. Considering the treated alone, the probability to stayincreases by 28% after the treatment. The difference between ATE and ATET is justified by the fact that the service provider actively targeted potential churners.

As for the second point, we compare their average monthly expenditure before and after the treatment, distinguishing by sim score, a 1 to 6 quality indicator assigned by the company to customers, where 1 indicates the best customers.[22] Table 8 shows customers'

[20] By allowing the use of each unit as a match more than once, matching with replacement reduces bias and makes the order in which individuals are matched irrelevant. Still, the number of times a control is matched should be accounted for to ensure that the treatment effect is not based on a few numbers of controls (Stuart, 2010).

[21] Formally, ATE $= E[Y_{1A} - Y_{0A}]$ while ATET $= E[Y_{1A} - Y_{0A} \mid T = 1]$. ATE can be interpreted as a weighted average of ATET and a treatment effect for the control group. When the treatment is randomly assigned and the sample is large enough, there is no difference between ATE and ATET. Instead, when the treatment is not randomly assigned, the difference between ATE and ATET represents the inherent differences between the treated and the controls, i.e. the selection bias associated with the treatment.

[22] Differently from the spending level, the score sim is more rigid to sudden variations because it is computed considering a six month window adjusted every three months.

Table 7
The results of the treatment (outcome: dummy = 1 if the client stays).

	obs(1)	coeff.	p>|z|	treated	controls(2)
ATE	151,242	0.39	0.000	17,000	13,800
ATET	151,242	0.28	0.000	17,000	13,800

Note (1): We lost 762 observations because no exact matching on the factor variables was found.
Note (2): The replacement option allows for one control subject to be assigned to more than one treated subject. The 17,000 treated in the sample have been matched to 13,800 controls, 82% of which have been used once, 15% twice, 3% more than twice.

Table 8
Customers' average monthly expenditure by group and sim score.

sim score class	anti-churn	obs. (%)[a,b]	mean	sd	min	med	max
1(best customers)	*1 pre*	93 (0.5)	50.6	33.6	1.5	44.6	137.7
	1 post	108 (0.7)	30.8	29.1	0	27.3	170.8
	0	1621 (2,1)	38.3	32.0	0	34.1	339.9
2	*1 pre*	478 (2.8)	22.7	15.1	0	21.2	122
	1 post	398 (2.5)	11.1	11.3	0	8.0	52.8
	0	4090 (5,3)	16.8	13.6	0	14.9	198.0
3	*1 pre*	1921 (11.3)	12.1	9.0	0	10.9	74.2
	1 post	1398 (8.7)	4.5	6.4	0	1.5	59.0
	0	9627 (12.6)	8.1	7.8	0	6.1	76.8
4	*1 pre*	6698 (39,4)	6.1	4.8	0	5.3	76.15
	1 post	5866 (36.3)	2.5	3.8	0	1.1	79.1
	0	26580 (34,8)	3.4	4.8	0	1.5	122.2
5	*1 pre*	7595 (44,7)	1.5	2.1	0	1.0	64.56
	1 post	8052 (49.9)	0.7	1.7	0	0.1	56.6
	0	24636 (32.2)	1.3	3.0	0	0.4	115.1
6 (worst customers)	*1 pre*	215 (1.2)	1.3	4.6	0	0.1	48.1
	1 post	748 (4.6)	1.3	5.2	0	0.2	61.6
	0	9909 (13.0)	1.7	8.8	0	0	196.9

[a] The percentage for the non-treated is calculated on a total of 76,463 subjects, which excludes the deactivated and the new sims.
[b] The percentage for the treated post-treatment is calculated on a total of 16,140 subjects, which excludes the deactivated sims.

average monthly expenditure per sim score class, separately for the treated (pre and post-treatment) and the controls.

As expected, the average monthly expenditure of the treated post-treatment is constantly lower than the one pre-treatment (except for worst customers), suggesting targeted customers are offered more convenient contracts.

5. Conclusions

Predicting consumer churn risk and developing appropriate retention strategies are major concerns of telecom companies and service companies more in general, as competition grows and service providers try to steal customers from their rivals. This paper has examined the efforts aiming at retaining customers, with a specific focus on the consumers' characteristics that make them ideal targets for companies' loyalty programs. In particular, starting from the observation that the relationship between customers' expenditures and churn is complex and the available evidence is inconclusive, we have examined the extent to which consumers' expenditures make them ideal targets for companies' loyalty programs. Our contribution has been both theoretical and empirical. On the theory side, we have developed a formal model to study the firms' incentives to offer a personalized pricing plan, when consumers are at risk of leaving and they are heterogeneous in service usage. The model predicts an inverted-U relationship between the usage intensity and the probability of being the target of a personalized offer. Concerning the empirical analysis, we have relied on an original dataset of customers of one of the top mobile network operators in the Italian market to empirically test the relationship between the intensity of service usage and the likelihood of the "treatment" (i.e. anti-churn campaign). The results are consistent with the theoretical predictions of the model. In addition, we have examined the average effect of the treatment (anti-churn campaign) on the decision to stay or leave of the treated customers and the estimated effect of the campaign on all individuals. We find that in both cases the anti-churn campaign has a positive and significant effect on customers' retention.

Future research related to this topic could develop in several ways. From the theoretical point of view, the static model we developed could be complemented by a dynamic analysis, whereby firms build their installed base in the initial stage, anticipating the possibility to propose retention offers afterwards. Such a model would parallel Esteves (2014), in a context in which firms must predict churn intentions, instead of simply reacting to them. In the Supplementary Material, we sketch a two-period model, whose results on the nature of equilibrium are consistent with the approach we adopted in the static model of the present paper. That model could be extended to an infinite-horizon setting with overlapping generations of consumers. If firms can discriminate also between young and old consumers, we expect our results on the incentives to propose a personalized plan to hold in this context as well. Also, firms' ability to predict the propensity to churn could be made a parameter of the model or even endogenized, assuming it depends on firms' investments in prediction technologies (Agrawal, Gans, & Goldfarb, 2018). Finally, the model has focused on explaining firms' behavior.

Social welfare evaluation of firms' retention strategies is of obvious relevance, too. In our setting, a straightforward policy implication of the results is that personalized tariff plans always benefit consumers (as long as they can decide whether accepting the offer), but also that any policy favouring transparency in the market, raising consumers' awareness, is advantageous for consumers even if they do no switch, because it increases the probability that (convenient) retention offerings are made. Qualifying these normative suggestions in more complex settings, as the ones mentioned before, seems a promising avenue for research.

From the empirical point of view, replicating our exercise for other companies in the mobile telecom sector and for other industries would be important to understand the possible degree of heterogeneity in retention strategies across firms also in terms of efficacy. If such differences exist, one could try to correlate them with firms' observable characteristics, such as size, that is likely to determine the amount of information available to the firm to design its tariffs (Corrocher & Zirulia, 2010).

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.telpol.2020.102069.

Appendix A

Proof of Proposition 1. Initially, we will ignore the constraint $\overline{p} \geq \widehat{p}_\theta^*$and look for $\widehat{p}_\theta^*$ maximizing the firm expected profit.

Deriving (5), the first order condition is:

$$\frac{dE\Pi}{d\widehat{p}_\theta} \equiv \theta\left(1-2\widehat{p}_\theta\right) - \alpha(\theta)\frac{\theta^2}{2}\widehat{p}_\theta\left(4-9\widehat{p}_\theta+4\widehat{p}_\theta^2\right)=0 \tag{A1}$$

The second order derivative is $\frac{d^2E\Pi}{d\widehat{p}_\theta^2} \equiv -2\theta - \alpha(\theta)\theta^2(2-9\widehat{p}_\theta+6\widehat{p}_\theta^2)$, which is negative in $\widehat{p}_\theta = 0$ and increasing in $\widehat{p}_\theta$. Since $\frac{dE\Pi}{d\widehat{p}_\theta}$ is positive in $\widehat{p}_\theta = 0$ and negative in $\widehat{p}_\theta = \frac{1}{2}$, the solution $\widehat{p}_\theta^*$ to (A1) exists, it is unique and corresponds to a global maximum.

To study how $\widehat{p}_\theta^*$ is affected by θ, we use of the implicit function theorem on $(1-2\widehat{p}_\theta) - \alpha(\theta)\frac{\theta}{2}\widehat{p}_\theta(4-9\widehat{p}_\theta+4\widehat{p}_\theta^2) = 0$,which yields:

$$\frac{d\widehat{p}_\theta^{\;*}}{d\theta} = \frac{\frac{1}{2}[\alpha'(\theta)\theta+\alpha(\theta)]\left[\widehat{p}_\theta\left(4-9\widehat{p}_\theta+4\widehat{p}_\theta^2\right)\right]}{-2-\alpha(\theta)\theta\left(2-9\widehat{p}_\theta+6\widehat{p}_\theta^2\right)} \tag{A2}$$

The denominator is negative for second order condition to be satisfied, while the sign of the numerator depends on the sign of $\alpha'(\theta)\theta+\alpha(\theta)$, For $\theta \to \underline{\theta}$, $\alpha'(\theta)\theta+\alpha(\theta)$ is positive; $\alpha'(\theta)\theta+\alpha(\theta)$ is decreasing is θ; for $\theta \to \overline{\theta}$, $\alpha'(\theta)\theta+\alpha(\theta)$ can be positive or negative. It follows that there are two possible situations: i) $\frac{d\widehat{p}_\theta}{d\theta}$ is always negative; ii) $\frac{d\widehat{p}_\theta}{d\theta}$ is first negative and then positive. By considering the constraint $\overline{p} \geq \widehat{p}_\theta^*$, we identify the consumers receiving a retention offer as summarized in the Proposition.

As mentioned in Section 3.1, two assumptions are critical for our results: i) the marginal impact of a price variation on consumer net surplus is stronger for high types; ii) a negative relationship between consumer type and awareness probability exists. To see why i) is important, assume that firm (erroneously) think that θ does not affect the probability of switching. It follows that the implicit function theorem would be applied to $(1-2\widehat{p}_\theta) - \frac{\alpha(\theta)}{2}\widehat{p}_\theta(4-9\widehat{p}_\theta+4\widehat{p}_\theta^2) = 0$,and since $\alpha'(\theta) < 0$, we would have $\frac{d\widehat{p}_\theta^{\;*}}{d\theta} > 0$ for any θ. As for ii), if $\alpha'(\theta) = 0$ for any θ, we would have $\frac{d\widehat{p}_\theta^{\;*}}{d\theta} = \frac{\frac{1}{2}[\alpha(\theta)][\widehat{p}_\theta(4-9\widehat{p}_\theta+4\widehat{p}_\theta^2)]}{-2-\alpha(\theta)\theta(2-9\widehat{p}_\theta+6\widehat{p}_\theta^2)}$ <0.

Appendix B

Table B1
Tariff plans

Name	Flat Tariff/ Monthly tariff	Internet	Voice (price per minute - cents)	SMS (cent)	MMS (euro)	Call connection fee (cent)	Other features
49E	1,96	6 euro up to 5 GB, then 2 euro per 100 MB	22,08 for all mobile and fixed numbers	29	1,3	18,9	Subscribers get a free top-up after reaching a monthly spending threshold, either with voice traffic or SMS.
49F							For 18 euros every four weeks: 400 min and 100 SMS to all national numbers and 3 GB in 4G, in addition to streaming music from selected services without consuming GB.
499	1,96			29	1,3		

(continued on next page)

Table B1 (*continued*)

Name	Flat Tariff/ Monthly tariff	Internet	Voice (price per minute - cents)	SMS (cent)	MMS (euro)	Call connection fee (cent)	Other features
		6 euro up to 5 GB, then 2 euro per 100 MBGB	30,15 for all mobile and fixed number				The rates are calculated on the actual seconds of conversation and the fractions are rounded up to the next second.
49Q	1,96	6 euro up to 5 GB, then 2 euro per 100 MBGB	13,01 for Vodafone's numbers, 22,08 for the others	29	1,3	21,07	Calls made to all national numbers and to a selection of countries share the same rate up to a maximum threshold of minutes per month.
498	1,96	6 euro up to 5 GB, then 2 euro per 100 MB	7,97 for 4 Vodafone numbers; 19,06 for other Vodafone numbers; 45,27 for other operators	29	1,3	19,06	The call rates are charged in advance, every 60 s.
49H	1,96		22,08	29	1,3	19,06	If you top up at least 10 euros, you will have 2000 min, to be used in a month, to call all Vodafone numbers at 0 cents per minute.
48A	1,96		13,01 for Vodafone numbers and fixed numbers; 45,27 for others	29	1,3	19,06	The call rates are charged in advance, every 60 s.
49S	1,96	6 euro up to 5 GB, then 2 euro per 100 MB	10,99 for Vodafone numbers; 35,19 for others	29	1,3	21,07	The call rates are charged in advance, every 60 s.
49L	1,96	6 euro up to 5 GB, then 2 euro per 100 MB	19,06	29	1,3	19,06	The call rates are charged in advance, every 60 s. Calls to the You & Me number cost 7.97 cents per minute, with a connection fee of 19.06 cents.
49R	Flat	30,55 cent a day up to100 MB	21,07	29	1,3	19,05	Subscribers have every day: 1000 free minutes of calls and 1000 min of video calls to all the numbers of the provider after the first minute of each call and 100 SMS and 100 free MMS after the first.
49T	1,96	6 euro up to 5 GB, then 2 euro per 100 MB	18,90 from 6pm to 8am and on Sundays/holidays; 29,90 for others time slots and days	29	1,3		To activate the18.90 cents per minute rate, subscribers should top up at least € 15 a month. If they do not top up for 30 days, they pay the basic rate of 29.90 cents per minute, until the next top-up
491	1,96	6 euro up to 5 GB, then 2 euro per 100 MB	13,90 from 4pm to 8 a.m. and on Sundays/holidays; 39,90 other time slots. 7,90 for You and Me	29	1,3	18,90	
492	1,96	6 euro fino a 5 GB, poi 2 euro per 100 MB	12 cents from 8am to 2pm, from 10pm to 8am and on Sundays/holidays; 36 cents from 2 p.m. to 10 p.m.	29	1,3	10	

Appendix C

Table C1
probit regression testing the determinants of treatment

DV = anti-churn	coeff.	std. err.	[95% conf. interval]	
log(average monthly expenditure)	0.97***	0.01	0.94	0.99
log(average monthly expenditure)^2	−0.25***	0.00	−0.26	−0.24
age	0.00***	0.00	0.00	0.00
gender	−0.10***	0.01	−0.12	−0.08
residency				
north-west	−0.04**	0.01	−0.07	−0.01
north-east	−0.01	0.01	−0.04	0.02
south	0.03*	0.01	0.01	0.06
tariff plan	yes			
constant	−1.31***	0.03	−1.37	−1.24
observations	151,345			
R^2	0.13			

Note: p-value<0.05*, <0.01**, <0.001***.

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