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

Giovanna Capponi
Nicoletta Corrocher
Lorenzo Zirulia

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Abstract

This paper analyses firms' strategies aiming at retaining customers, with a specific focus on 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 formal, economic model to study the firms' incentives to offer personalized pricing plan, when consumers are at risk of leaving and they are heterogenous in service usage. The model predicts an inverted-U relationship between usage intensity and the probability of being the target of a personalized offer. Our empirical results, based on an original dataset of customers of one of the top mobile network operators in the Italian market, confirm the theoretical prediction,

Keywords: personalized pricing, churn rate, mobile communications

1. Introduction

Customer retention is one of the most important concerns for firms in search of competitive advantages in mature sectors like the telecom industry. The increasing availability of information and the possibility of comparing prices across different telecom operators makes it easier for customers to change provider and makes it more and more difficult for companies to find appropriate strategies to reduce the churn rate (Lejeune, 2001). Despite the substantial effort in developing customer loyalty programs and ad-hoc offerings for existing customers, churn rate is still significant. In 2018, the customer churn rate in the telecom industry in the US was 21%[1], while this figure was on average 28.5% for a major European wireless operator.

Customer churn is the outcome of competing firms' conflicting strategies. On the one hand, customers' dissatisfaction on pricing is a major churn determinant in the telecom service sector (Keaveney, 1995; Kim et al., 2004). As a consequence, firms can try to steal customers from competitors by offering special discounts and proposing them other incentives to switch (Fudenberg and Tirole, 2000). In the telecom industry, operators have tested their pricing schemes to optimize profits in a highly competitive contexts (Genakos et al., 2015), sometimes at the expense of foggy information for customers (Miravete, 2013). However, the process of customer poaching is hindered by different types of switching costs, which persist in the industry despite number portability (Farrell and Shapiro, 1998; Ahn et al., 2006; Lee et al., 2006; Gerpott et al., 2008; Grzybowski, 2008; Corrocher and Zirulia, 2010).

On the other hand, as customer defection grows, companies have invested in different mechanism to maintain loyalty, such as free phones, upgrades, free minutes and lock-in to the handset (Eshghi et al., 2007). This is particularly important because, if a customer switches, a company loses future revenue streams, and, more than this, if the customer is an old (loyal) one, the loss is from the high-margin segment of the customer base (Keaveney, 1995). One way of strengthening customer loyalty for telecom companies is to propose personalised pricing (Wong, 2010; Richards et al., 2016). The use of this strategy enhances retention because, among other things, it allows companies to reduce the uncertainty associated to people behaviours, which usually affects what is consumed

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

and charged (Genakos et al., 2015). The emergence of artificial intelligence and machine learning technologies together with the availability of customer-related big data has increased the application of data analytics for this purpose, with a growing number of companies are expanding their competencies in real-time customer analytics not only to improve customer experience, but above all to sustain customer loyalty (Spiess et al., 2014; Ervelles et al., 2016; Anshari et al., 2019). Through these technologies, companies can leverage data through diagnostic, prescriptive, and predictive analytics. Adopting a proactive approach, the company identifies customers who are likely to churn and targets them with special promotions to keep them from churning. Many studies utilized various data mining techniques to assist telecom companies in resolving churn problems (Hung et al. 2006; Kim et al., 2004; Kim et al., 2005; Wei et al., 2002).

Starting from these considerations, the aim of this paper is to analyze firms' strategies aiming at retaining customers, with a specific focus on 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 formal, economic model to study the firms' incentives to offer personalized pricing plan, when consumers are at risk of leaving and they are heterogenous in service usage. How much consumers spend for the service can affect both their value for the company and their propensity to switch, which may explain why the evidence concerning the impact of consumers' expenditure on the churn rate is rather inconclusive (Madden et al., 1999; Mozer et al., 2000; Kim and Yoon, 2004; Ahn et al., 2006; Seo et al., 2008). The model predicts an inverted-U relationship between usage intensity and the probability of being the target of a personalized offer. On one side, light users are less valuable, so that reducing the price they pay to retain them is not convenient. On the other hand, high-spending users may have a lower propensity to switch. This may be the case if such consumers are less informed about alternative plans offered by competing firms, which may occur if larger expenditures are driven by higher income, and higher income entails softer budget constraints and larger search costs (Urbany et al., 1996; Mehta et al., 2003); or because they are less sophisticated, users, so that they spend more also due to their "naiveté" (Bolle and Heimel, 2005; Lambrecht and Skiera, 2006; Corrocher and Zirulia, 2009; Haucap and Heimeshoff, 2011).

On the empirical side, the paper uses an original dataset of customers of one of the top mobile network operators in the Italian market. 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. We have information on socio-demographic variables and on monthly expenditures over a five-month period. Our results confirm the theoretical prediction, since we find an inverse U-shape between average monthly expenditure and the probability to be targeted, controlling for individual characteristics and the current tariff plan. In addition, 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 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.

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 (Keaveney, 1995S; Stewart, 1998; Chandar et al., 2006). Even if companies always attempt to strenghten their customer base while acquiring new clients, the number of churning customers grows as the market becomes more mature, since competition becomes more intense and more information is available and easily accessible to the customers. As customers become more aware of the different opportunities available in the market, and the comparison of different products or services is relatively cheap and easy, companies become more sensitive about churn. The increase in customer churn causes a decrease in profit level, and consequently, makes a company lose a privileged position in the market (Reichheld and Sasser, 1990).

Since the churn rate depends on the industry life-cycle, when an industry is growing, the number of new customers exceeds the number of churners. In the maturity phase, companies put more effort into customer retention and on churn reduction, by developing loyalty programs (Lejeune, 2001).

The literature has largely looked at the determinants of customer churn (Keaveney, 1995; Gerpott et al., 2001; Chakravarty et al., 2004; Kim and Yoon, 2004; Ahn et al., 2006; Eshghi et al., 2007; Seo et al., 2008). The existing studies identify two main sets of factors determining churn in the telecom sector: the specific features of the service (e.g. call quality, price, contract duration) and the individual characteristics (socio-demographic characteristics, usage intensity and monthly expenditure).

As far as the first set of factors is concerned, the retention of customers depends on the level of satisfaction with alternative specific service attributes such as call (network) quality, tariff/price level, handset characteristics and brand image (Gerpott et al., 2001; Kim and Yoon, 2004; Lee et al., 2006; Calvo-Porral et al., 2015). Similarly, 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). Seo et al. (2008) showed that a complex service plan, a sophisticated handset, long-term contracts and high quality of service are positively related to customer retention. Furthermore, membership card programs have a significant negative impact on the probability of customer churn.

With reference to the second set of factors, service usage is often indicated as one of the most relevant behavioural predictors of churn (Madden et al., 1999; Mozer et al., 2000), and for that reason will be the main focus of our theoretical and empirical contribution. The literature has provided some evidence on the fact that heavy spenders are more likely to churn (Ahn et al., 2006; Seo et al., 2008), a result that can be accounted for as long as customers that spend more are more price-sensitive and tend to explore different services. However, results are not conclusive and some works do not find a significant relationship between the amount of bills and the probability of churn when controlling for customer satisfaction indicators (Kim and Yoon, 2004).

Finally, it is important to stress that recently many studies utilized various data mining techniques to assist telecom companies in resolving churn problems (Hung et al. 2006; Kim et al., 2004; Kim et al., 2005; Wei et al., 2002).

Customer satisfaction affects customer loyalty, which is highly correlated with customer retention (Gerprott et al., 2001). However, there may be cases in which customers decide to stay with their operator even in case of low customer satisfaction, mostly due to the presence of switching costs (Chuang, 2011; Gerprott et al., 2001; Kim et al., 2004; Lee et al., 2006). The literature defines switching cost as the effort and expense customer face when switching from one product to another (Klemperer, 1987). Burnham et al (2003) identify three broad categories of switching costs:

- *Procedural costs*, which include managing transactions, learning costs, comparing alternatives and uncertainty.
- *Financial costs*, which incorporate penalties for cancelling a contract and losing loyalty discounts.
- *Relational costs*, which include the psychological and emotional costs of breaking the existing relations.

Even in the presence of number portability, switching costs are still significant in the mobile telecom industry. Contracts are usually 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). Consumers have to communicate their habitual contacts that they have changed operator since this change affects the cost of calls for those who call them. Switching costs can also emerge because operators can force consumers to use handsets exclusively within their own network, and unlocking comes at a cost. Furthermore, there are search costs because consumers have to gather information about other operators' tariff plans. Finally, switching costs can be also psychological, due to consumer inertia (Farrell and Shapiro, 1998; Ahn et al., 2006; Lee et al., 2006; Gerpott et al., 2008; Grzybowski, 2008; Corrocher and Zirulia, 2010).

In order to reduce the level of customers' switching to other service providers in a dynamic competitive environment, companies can develop strategies to respond to consumers' switching cost (Farrell and Shapiro, 1988; Zauberman, 2003). The literature focused extensively on the effects of switching on competition (Klemperer, 1987). Cabral (2016) shows that in a competitive environment switching costs have two different direct effects. First, they increase the market power of a seller with locked-in customers; second, they increase the rivalry between firms to get new customers, which may lead to an increase in retention techniques and in the competition. From a theoretical perspective therefore reducing switching costs does not always make a market more competitive because firms face trade-offs: on the one hand, they have incentives to set monopolistic prices for their existing users, but at the same time they have incentives to offer competitive prices in order to attract new users.

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

How do companies face the churn? 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 stay (Neslin et al., 2006; Coussement and Van den Poel, 2008).

In competitive markets, target approaches are adopted both firms willing to retain their own customers, and by firm trying to induce switching from competitors. These are example of behaviour-based price discrimination (Villas-Boas, 1999; Fudenberg and Tirole, 2000; Armstrong and Huck, 2010; Richards et al., 2016; De Nijs, 2017), whereby firms discriminate prices across different customers based on the observation of individual characteristics and past service usage patterns or purchasing behaviour. In the words of the Office of Fair Trade (OFT), personalised 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).

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 (Weisstein et al., 2013; OECD, 2018). Personalised 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 may decide to charge consumers a price which is lower than their willingness to pay. In particular, firms can set lower prices in order 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 own customers to capture surplus from them (Caillaud and De Nijs, 2014). However, while behaviour-based price discrimination is unambiguously profitable if adopted by a single firm, industry profits can fall if all firms practice it, and relatedly, from a policy perspective, banning behaviour-based price discrimination has an ambiguous effect on 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 will 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 behavior-based price discrimination has 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-Provide 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 in order to secure number portability. The main result of the paper concerns the welfare implication of behavior-based price discrimination with retention offers, as Esteves shows that such a pricing strategy is beneficial for consumer and overall surplus, but detrimental to industry profit. Our model, instead, focuses of industries in which Gaining Provider Led process applies, such the Italian mobile communication industry, in which the current firm is not informed about the consumer intention to switch until the contract is signed. In this case, firms can only to predict which customers are at higher risk of leaving, and offer targeted promotional offers if it is profitable to so.

3. Personalized pricing for customer retention: a formal model

3.1. Model description

Let us consider a mature telecom market where $n \geq 3$ firms (i.e. telecom operators) offer a homogenous product (the telecom service) at zero marginal cost. *i* is the index for the generic firm. Each firm has an installed base of consumers and a current offer of different tariff plans. m_i is the number of different tariff plans offered by firm *i*, and *j* is the index for the generic plan, so that S_{ij} is the mass of consumers attached to tariff plan *j*, offered by firm *i*. Although tariff plans in telecom markets are usually multi-dimensional, for simplicity we will identify them with a single (linear) price $\bar{p}_{ij}$, which stands for tariff plan j offered by firm *i*. Each consumer *k*, attached to tariff plan *j* offered by firm *i*, is identified by a type θ_{kij}. Consumers' type θ is 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 given price p, the consumer net surplus is $\frac{\theta}{2}(1-p)^2$. In addition, given (2), $\frac{1}{2}$ is the monopoly price for any θ, so that we restrict our attention to $\bar{p}_{ij} \leq \frac{1}{2}$.

We shall assume that firms can perfectly observe the consumers' type in their installed base, while other firms cannot. Within tariff plan j offered by firm i, types are distributed according to a certain density function $g_{ij}(\cdot)$, over the support $[\underline{\theta}_{ij}; \overline{\theta}_{ij}]$.

Since we are interested in retention pricing strategies, we rule out the possibility that firms can change the set of tariff plans available to all their existing consumers (i.e. $\bar{p}_{ij}$), or that consumers can switch to other tariff plans offered by their current firm. Instead, our focus lies on two pricing decisions. First, we denote with $\hat{p}_{\theta ij}$ the personalized tariff plan, if any, offered to consumer of type θ attached to tariff plan j offered by firm i. We will refer to such a plan also as the customer retention offer. We shall assume that firms cannot impose a personalized tariff plan to customer k, so that the personalized offer will be accepted only if $\hat{p}_{\theta ij} \leq \bar{p}_{ij}$. Second, we denote with $\tilde{p}_i$ the tariff plan that firm i offers to other firms' customers, which cannot be made contingent to type and tariff plan (which are not observable), nor restricted to consumers of a specific firm.[2] We will refer to such a plan also as the poaching offer.

Pricing decisions are sequential. In the first stage, firms (simultaneously) decides the tariff plan offered to other firms' customers. In the second stage, firms decide their customer retention offers. Firms' maximize their expected profit. The relevant equilibrium concept in the game is then subgame perfection (SPE).

We made two key assumptions concerning the customer *switching behaviour*. In particular, $\alpha_{ij}(\theta)$ is the probability that a consumer of type θ attached to tariff plan j offered by firm i actually observes $\tilde{p}_z$, with $z \neq i$. We will define such consumers as *aware*. In addition, for those observing $\tilde{p}_z$, changing firm entails a switching cost σ, which has with uniform distribution over the unit interval, irrespectively of θ, j and i. Firms does not observe the switching cost, but know its distribution. Switching occurs if

[2] Relaxing this assumption will be inconsequential for our results, since, as we will show, firms always have the incentive to fix the lowest possible price for consumers which are not currently serving.

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. Let us define $\widetilde{p}_{-i}^{min}$ as the lowest poaching offer by firms different from i. Then, for a generic price p_i the probability of switching is given by $\Pr\left(\sigma < \frac{\theta}{2}\left[p_i(2-p_i) - \widetilde{p}_{-i}^{min}(2-\widetilde{p}_{-i}^{min})\right]\right) = \frac{\theta}{2}\left[p_i(2-p_i) - \widetilde{p}_{-i}^{min}(2-\widetilde{p}_{-i}^{min})\right]$.[3]

The behaviour of $\alpha_{ij}(\theta)$ plays a key role in the model. In particular we shall assume that $\alpha'_{ij}(\theta) \leq 0$ and $\alpha''_{ij}(\theta) < 0$, with $\alpha_{ij}(\underline{\theta}) = 1$ and $\alpha'_{ij}(\underline{\theta}) = 0$.[4] In words, the fraction of aware consumers is supposed to be lower for high-spending customers. This may result from the combination of two different factors. First, high-spending consumers may be less *informed* about alternative plans offered by competing firms. which may occur if larger expenditures are associated to higher income, and higher income to softer budget constraints and larger search costs. For instance, Urbany et al. (1996) find that income a significant negative impact on price search effort in a sample of US consumers, while Mehta et al. (2003) identify a negative relation between per capita income and search costs, using scanner data for liquid detergents. [5]

Second, larger expenditure may be associated to a lower degree of customer *sophistication*. A recent theoretical and empirical literature in behavioral industrial organization has been developed on the premise of boundedly rational behaviour on the consumers' side (Spiegler, 2011) and a bunch of empirical papers has shown that this can particularly be the case in telecommunications market. Lambrecht and Skiera (2006) consider the choice between a flat rate and a pay-per-use tariff, and show that users often choose the wrong tariff plan based on their actual behaviour, with evidence for the existence of both a flat-rate bias (when a flat rate is chosen, but pay-per-use tariff would have been more convenient) and a pay-per-use bias (the opposite case). Grubb and Osborne (2015) show that mobile phone users are inattentive to past usage, which can be costly in presence of overage charges, and some commit mistakes in their tariff plan choice because they underestimate the variance of their future consumption. Other

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

[4] The assumption on $\alpha''_{ij}(\theta)$ can be relaxed as long as it is negative for sufficiently low values of θ.

[5] In our context, consumer type has a positive impact on the search benefit side, so that the overall effect is 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.

specificities of telecom pricing may trigger sub-optimal choices. In presence of on-net/off-net price differentials, Bolle and Heimel (2005) and Haucap and Heimeshoff, (2011) show that users can make the wrong choices if they fail to estimate correctly the probability of on-net and off-net calls for a given operator. Relatedly, Corrocher and Zirulia (2009) show that consumers are heterogenous in the importance they attach to the operators chosen by their friends and family members in choosing which provider to use, and that consumers that are more interested in this form of local network effects tend to spend relatively less given their usage intensity. Following this discussion, we expect less sophisticated users to spend more; and if lower sophistication entails also a lower attention towards other firms' offer, a lower fraction of aware users will be observed among high-spending users.

3.2. Results

The solution of the pricing game is simplified by Lemma 1, whose proof is Appendix A.

Lemma 1 *In any SPE, $\hat{p}^{*}_{\theta i j} > 0$ and $\tilde{p}^{min,*}_{-i} = 0$, for any θ, i and j.*

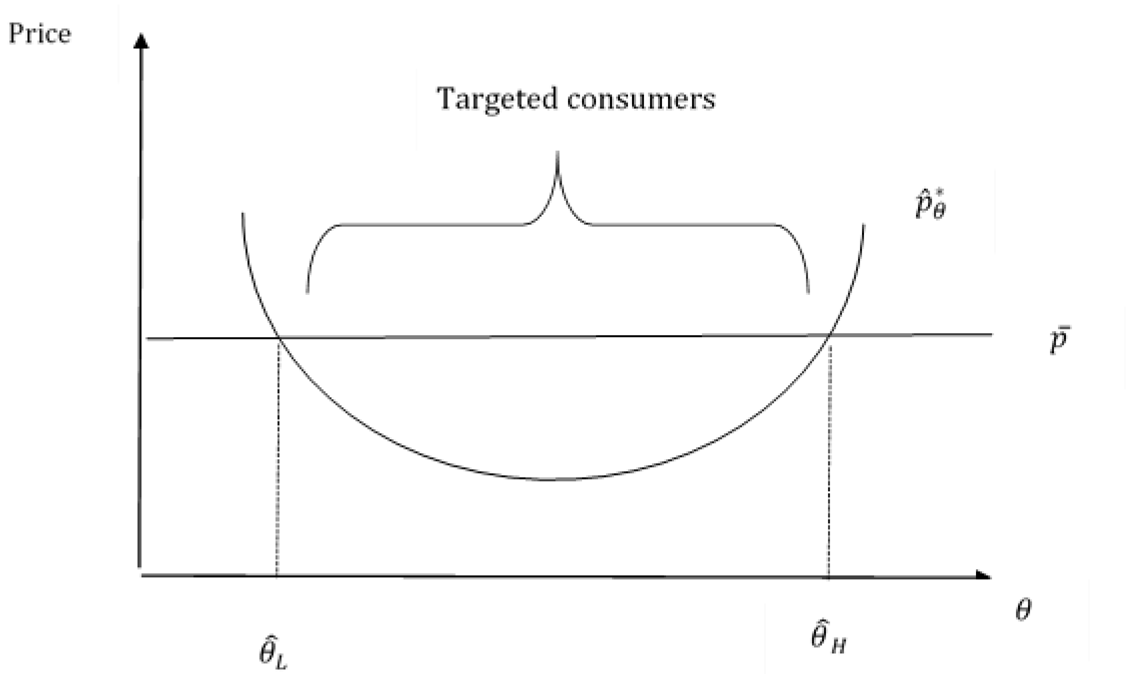
The intuition behind Lemma 1 is straightforward. On one hand, Bertrand-type competition for consumers attached to a specific firm, involving the other operators, lead the poaching offer to the lowest possible price (i.e. marginal cost). On the other hand, a firm will never make a personalized offer matching poaching offers equal to zero, because by fixing a small, positive price it would secure a positive market share, and then a positive profit, due to the existence of switching cots and imperfect awareness.

Following Lemma 1, from now on we will focus on a generic firm offering a given tariff plan, and therefore we will omit indexes *i* and *j* for the sake of simplicity. The proof of Proposition 1 is in Appendix A.

Proposition 1 *There are two thresholds, $\hat{\theta}_L \geq \underline{\theta}$ and $\hat{\theta}_H \leq \overline{\theta}$, with $\hat{\theta}_L \leq \hat{\theta}_H$, such that consumers with $\hat{\theta}_L < \theta < \hat{\theta}_H$ receive a retention offer.*

In words, Proposition 1 says that, in general, retention offer are made to consumers whose type is not too low not too high. First of all, it is important to remind 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 which 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 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 an offer to them runs the risk of targeting high-spending consumers that would not switch anyway. Thus, the firm targets the segment $(\hat{\theta}_L,\ \hat{\theta}_H)$, i.e. the valuable and aware consumers. Figure 1 represents graphically the set of targeted consumers, by depicting the optimal personalized price and the current tariff plan.

Figure 1 – Targeted consumers



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

The main goal of this section is to test the prediction of our theoretical model concerning the characteristics of consumers who made them target of anti-churn campaigns. A limitation of our data is that we do not have information about the characteristics of the retention offers, and if targeted consumers accept them or not. For that reason, we are also going to show evidence on the effect of churn prevention campaigns, which are in line with our theoretical framework.

4.1. Dataset and variables' description

The dataset consists of 152,004 prepaid sim cards of one of the top mobile network operators in the Italian market, which may or may not have been targeted for churn prevention campaigns between November 2012 and March 2013. Specifically, the sample entails 17,000 targeted records and 135,004 cases which were not targeted for any campaign during the reference time; 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 a three months period both before and after this event. Instead, the time span for non-targeted sim cards covers the reference period November 2012 – March 2013. The overall composition of the dataset is as follows:

Table 1: Dataset composition

Anti-churn Campaign	***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

Telecommunication service providers largely rely on call patterns to identify potential churners (Wei and 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. Other relevant variables cover contract characteristics and customer demographics. For the purpose of this study, we consider information concerning the tariff plan, customers' age, gender and region of residence. Table 2 summarizes the main variables.

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
Region of 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.[6] Table 3 shows that the targeted customers are better clients, i.e. clients with higher average monthly expenditures: 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.[7] This descriptive evidence is a first support to our theoretical prediction.

6 Note that targeted and non-targeted customers are not observed over the same time 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 which are still active at the end of the period, the outcome does not change. Detailed results are available upon request.

[7] This interpretation is also supported by the higher standard deviation reported.

Table 3: Average monthly expenditure per group

Anti-churn campaign	*N°. 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	

The other predictors of interest are demographic variables, which are likely to affect customers' quality and loyalty (Gerpott et al., 2001; Kim and Yoon, 2004; Ahn et al., 2006**;** 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.

Table 4: Age distribution

Anti-churn campaign	*N°. 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 *(N° of customers)*

	Anti-churn campaign	
Residence	*Yes*	*No*
North west	4,103	34,035
North east	4,069	29,111
Centre	3,934	31,520
South	4,894	40,334
Total	152,000	100

Finally, we look at the tariff plan, as a control for the price paid by customers. Table B1 in the Appendix shows the characteristics of the 16 tariff plans of our customers.

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 to be targeted for the anti-churn campaign. Given the right-skewed distribution of the average monthly expenditure, we log-transform the variable. Also, to account for non-linear relationships between the continuous covariates and the dependent variable, we include their square terms. The regression results are reported in Table 6.

Table 6: logit regression testing the determinants of treatment

Treatment	Odds Ratio	Std. Err.	z	P>z	Conf. Interval]	
log(AME)	6.396	0.171	69.24	0.000	6.069	6.741
(log(AME))2	0.611	0.005	-55.55	0.000	0.600	0.622
Age	1.050	0.004	13.55	0.000	1.043	1.058
Age2	1.000	0.000	-11.93	0.000	0.999	1.000
Gender	0.836	0.014	-10.34	0.000	0.809	0.865
Residency						
1	0.909	0.023	-3.81	0.000	0.865	0.955
2	0.970	0.025	-1.22	0.223	0.923	1.019
4	1.061	0.026	2.41	0.016	1.011	1.113
Bundle						
14M	1.000	(empty)				
48A	0.804	0.042	-4.19	0.000	0.726	0.890
491	0.751	0.052	-4.11	0.000	0.655	0.861
492	1.266	0.281	1.06	0.288	0.820	1.954
498	0.418	0.039	-9.45	0.000	0.349	0.501
499	0.511	0.025	-13.53	0.000	0.463	0.563
49E	0.693	0.038	-6.67	0.000	0.622	0.772
49F	1.096	0.075	1.33	0.184	0.957	1.254
49G	1.000	(empty)				
49H	0.607	0.049	-6.19	0.000	0.518	0.711
49L	1.037	0.076	0.49	0.622	0.898	1.196
49Q	0.798	0.054	-3.31	0.001	0.698	0.912
49R	0.298	0.018	-19.66	0.000	0.264	0.336
49S	0.262	0.013	-27.51	0.000	0.238	0.288
49T	1.000	(omitted)				
50	1.000	(empty)				
_cons	0.038	0.004	-32.3	0.000	0.031	0.046
R2	0.1273					
No. obs	151345					

Consistently with our model, we observe that an increase in the average monthly expenditure increases the probability of a customer to be targeted at a decreasing rate, as the odds ratio of the squared term is lower than 1[8]. Specifically, the U-shape test proposed by Lind and Mehlum (2010) confirms the presence of an inverse U-shape between average monthly expenditure and the probability to be targeted. A unitary increase in Age increases the odds of being targeted by 5%. We also observe that for a male, the odds to be treated are 17% lower than for a female. Lastly, considering customers whose residency is the central regions as a reference (residency=3), we note that the south of the country is more likely to be targeted, the northern regions less.

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 if 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, in order to be accepted, such offers should be more convenient for users with respect 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 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 to the outcome across the two groups (Rosenbaum, 1999, 2002). 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

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8 Note that the coefficient of log(AME) in log odds is log(6.39). A 1% increase in AME 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 AME increases by 1% the odds for a customer to be treated increase by 2%.

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 and Thomas, 1996). 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 (Rubin, 1973a, Abadie and Imbens, 2006), which is a non-parametric estimator assigning the control case *j* with the shortest distance *Dij* to treated individual *i,* with replacement[9] . The distance *Dij* is defined using Mahalanobis distance on continuous variables, namely log(AME) 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.[10] Table 7 shows that in both cases, the anti-churn campaign has a positive and significant effect on 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 effect on the probability to stay is 28%. Clearly, the difference between ATE and ATET is justified by the fact that the service provider actively targeted potential churners.

9 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).

10 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.

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

	No. 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.

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 to clients, where 1 indicates the best clients.[11] Table 8 shows customers' average monthly expenditure per sim score class, separately for the treated (pre and post-treatment) and the controls.

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

Sim score class	*Treatment*	*Obs. (%)*[12][13]	*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

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

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

[13] The percentage for the treated post-treatment is calculated on a total of 16,140 subjects, which excludes the deactivated sims.

	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

As expected, the average monthly expenditure of the treated post-treatment is constantly lower than the one of the control group, suggesting targeted customers are offered more convenient contracts. Looking at the number of observations in each class, we notice that a relatively higher percentage of clients is targeted from classes 4 and 5, confirming the previous evidence whereby very good or very bad clients are less likely to be targeted. Moreover, we observe that, with the exception of class 6, the average monthly expenditure of the treated group pre-treatment is systematically higher than the value for the controls, showing that the churn prevention campaign was somehow addressing the best clients within each class.

6. Conclusions

This paper has analysed firms' strategies aiming at retaining customers, with a specific focus on consumers' characteristics that make them ideal targets for companies' loyalty programs. Our contribution has been both theoretical and empirical. On the theory side, we developed a formal, economic model to study the firms' incentives to offer personalized pricing plan, when consumers are at risk of leaving and they are heterogenous in service usage. The model predicts an inverted-U relationship between usage intensity and the probability of being the target of a personalized offer. Our empirical results, based on an original dataset of customers of one of the top mobile network operators in the Italian market, confirm the theoretical prediction,

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Appendix A

Proof of Lemma 1 We first show that if $\tilde{p}_{-i}^{min,*} \geq 0$, then $\hat{p}_{\theta ij}^{*} = 0$ cannot be an equilibrium. Firm i's expected profit is written as:

$$E\Pi_i = \theta\big(1 - \hat{p}_{\theta ij}\big)\hat{p}_{\theta ij} - \alpha(\theta)\frac{\theta^2}{2}\big(1 - \hat{p}_{\theta ij}\big)\hat{p}_{\theta ij}\big[\big(2 - \hat{p}_{\theta ij}\big)\hat{p}_{\theta ij} - \big(2 - \tilde{p}_{-i}^{min}\big)\tilde{p}_{-i}^{min}\big] \qquad \text{(A1)}$$

The first order derivative is:

$$\frac{dE\Pi}{d\hat{p}_{\theta ij}} = \theta\big(1 - 2\hat{p}_{\theta ij}\big) - \alpha(\theta)\frac{\theta^2}{2}\Big\{\big(1 - 2\hat{p}_{\theta ij}\big)\big[\big(2 - \hat{p}_{\theta ij}\big)\hat{p}_{\theta ij} - \big(2 - \tilde{p}_{-i}^{min}\big)\tilde{p}_{-i}^{min}\big] + 2\big(1 - \hat{p}_{\theta ij}\big)^2\hat{p}_{\theta ij}\Big\} \qquad \text{(A2)}$$

which is positive in $\hat{p}_{\theta ij} = 0$.

Secondly, we show that if $\hat{p}_{\theta ij}^{*} > 0$, then $\tilde{p}_{-i}^{min,*} > 0$, then cannot be true in equilibrium. If there is a firm $z \neq i$ such that $\tilde{p}_{-i}^{min,*} > \tilde{p}_z$, firm z has the incentive to reduce its price below $\tilde{p}_{-i}^{min,*}$ to firm *i*'s users with a positive probability. If $\tilde{p}_{-i}^{min,*} = \tilde{p}_z$ for all $z \neq i$, these firms have the incentive to slightly reduce their poaching offer, increasing the probability to acquire firm *i*'s users and so their profit. This completes the proof.

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

Given Lemma 1, the first order condition becomes:

$$\frac{dE\Pi}{d\hat{p}_\theta} \equiv \theta(1 - 2\hat{p}_\theta) - \alpha(\theta)\frac{\theta^2}{2}\hat{p}_\theta\left(4 - 9\hat{p}_\theta + 4\tilde{\hat{p}}_\theta^2\right) = 0 \qquad \text{(A3)}$$

The second order derivative is $\frac{d^2E\Pi}{d\hat{p}_\theta^{\,2}} \equiv -2\theta - \alpha(\theta)\theta^2\left(2 - 9\hat{p}_\theta + 6\tilde{\hat{p}}_\theta^2\right)$, which is negative in $\hat{p}_\theta = 0$, increasing in $\hat{p}_\theta$. Since $\frac{dE\Pi}{d\hat{p}_\theta}$ is positive in $\hat{p}_\theta = 0$ and negative in $\hat{p}_\theta = \frac{1}{2}$, the solution $\hat{p}_\theta^*$ to (A3) exists, it is unique and it is a global maximum.

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

$$\frac{d\hat{p}_\theta{}^*}{d\theta}=-\frac{[\alpha'(\theta)\theta+\alpha(\theta)]\left[\hat{p}_\theta\left(4-9\hat{p}_\theta+4\hat{p}_\theta^2\right)\right]}{-2-\alpha(\theta)\theta\left(2-9\hat{p}_\theta+6\hat{p}_\theta^2\right)} \tag{A4}$$

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

Appendix B

Table B1 – Tariff plans

Nome Piano	Tariffa flat/ Costo al mese	Internet	Voce (al minuto)	SMS (cent)	MMS (euro)	Scatto alla risposta (cent)	Features
49E	1,96	6 euro fino a 5 giga, poi 2 euro per 100 MB	22,08 cent verso tutti i numeri fissi e mobili	29	1,3	18,9	Subscribers get a free top-up after reaching a monthly spending treshold, either with voice traffic or SMS.
49F							For 18 euros every four weeks: 400 minutes and 100 SMS to all national numbers and 3 gigabytes in 4G, in addition to streaming music from selected services without consuming the Giga.
499	1,96	6 euro fino a 5 giga, poi 2 euro per 100 MB	30,15 cent verso tutti i numeri di rete fissa e mobile	29	1,3		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 fino a 5 giga, poi 2 euro per 100 MB	13,01 per i Vodafone, 22,08 per gli altri	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 treashold of minutes per month.
498	1,96	6 euro fino a 5 giga, poi 2 euro per 100 MB	7,97 verso 4 numeri vodafone; 19,06 verso altri Vodafone; 45,27 verso altri operatori	29	1,3	19,06	The call rates are charged in advance, every 60 seconds.
49H	1,96		22,08	29	1,3	19,06	If you top up at least 10 euros, you will have 2,000 minutes, to be used in a month, to call all Vodafone numbers at

							0 cents per minute.
48A	1,96		13,01 Vodafone e rete fissa; 45,27 altri	29	1,3	19,06	The call rates are charged in advance, every 60 seconds.
49S	1,96	6 euro fino a 5 giga, poi 2 euro per 100 MB	10,99 verso Vodafone; 35,19 altri	29	1,3	21,07	The call rates are charged in advance, every 60 seconds.
49L	1,96	6 euro fino a 5 giga, poi 2 euro per 100 MB	19,06	29	1,3	19,06	The call rates are charged in advance, every 60 seconds. 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 al giorno fino a 100 MB	21,07	29	1,3	19,05	Subscribers have every day: 1,000 free minutes of calls and 1,000 minutes 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 fino a 5 giga, poi 2 euro per 100 MB	18,90 dalle 18 alle 8 e domenica/festivi; 29,90 altri periodi	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