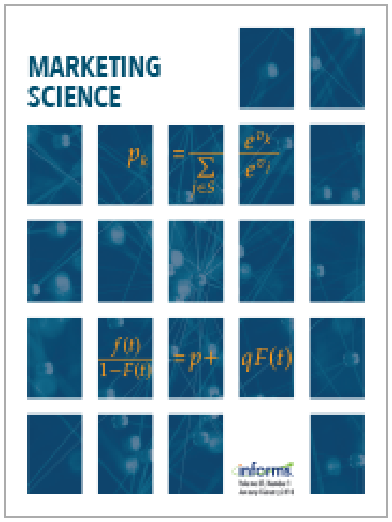

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Target the Ego or Target the Group: Evidence from a Randomized Experiment in Proactive Churn Management

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Abstract. We propose a new strategy for proactive churn management that actively uses social network information to help retain consumers. We collaborate with a major telecommunications provider to design, deploy, and analyze the outcomes of a randomized control trial at the household level to evaluate the effectiveness of this strategy. A random subset of likely churners were selected to be called by the firm. We also randomly selected whether their friends would be called. We find that listing likely churners to be called reduced their propensity to churn by 1.9 percentage points from a baseline of 17.2%. When their friends were also listed to be called, their likelihood of churn reduced an additional 1.3 percentage points. The client lifetime value of likely churners increased 2.1% with traditional proactive churn management, and this statistic becomes 6.4% when their friends were also listed to be called by the firm. We show that, in our setting, likely churners receive a signal from their friends that reduces churn among the former. We also discuss how this signal may trigger mechanisms akin to both financial comparisons and conformity that may explain our findings.

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Keywords: churn management • client lifetime value • social networks • randomized experiment

1. Introduction

Customer retention is a central concern in many industries, in particular in IT-related markets, in which churn rates are considerably high. For example, cell phone companies report churn rates as high as 2% per month (Bensoussan et al. 2014) and pay-TV firms experience churn rates of about 1% per month (Green 2016). Such high churn rates have a significant impact on the value and profitability of firms (Gupta et al. 2004). As a consequence, customer retention is a fundamental issue in marketing research. In general, there are two main approaches to manage customer churn: firms can either wait for consumers to request service to be disconnected and extend them aggressive retention deals when this happens—reactive churn management—or they can try to anticipate which consumers are likely to churn and reach out to them before they do—proactive churn management. Reactive churn management focuses on users who have already signaled their willingness to leave the firm. However, at that stage, it might be too late to convince them to stay. With proactive churn management, firms reach consumers sooner, which may be cheaper, but they may also extend deals to users who were unlikely to leave.

Proactive churn management is often viewed as a more sophisticated approach potentially leading to better results for the firm. However, it is still hard to generalize the effects of proactive churn management even within the telecommunications industry. Although some studies found that proactive churn management helps retain consumers, such as Burez and Van den Poel (2007) in the context of pay-TV services, others report an increase in the churn rate of the targeted consumers, such as Ascarza et al. (2016) in the context of prepaid mobile. In parallel, a number of studies have looked at the role of social networks in consumer decision making in the context of IT. However, only a few studies have looked at the impact of peer effects on churn. Nitzan and Libai (2011) analyzed a large data set from a cell phone provider and found that exposure to a churner is positively associated with churn. In a more recent study, Ascarza et al. (2017a) identified customers at risk in another cell phone provider and found that giving them a monetary credit increased usage and lowered churn across both the treated consumers and their connections. The authors attribute this result to the explicit network externalities associated to how consumers can use the gifted credit to place calls.

In this paper, we study a new strategy to retain consumers and compare its performance to that of traditional proactive churn management. Once proactive churn management may be profitable in pay-TV markets and IT-related services may benefit from peer influence, we ask whether it may be profitable for a telecommunications firm that offers triple-play service to combine churn management with peer effects. In particular, and in a context without explicit network externalities, does it help to reach out to the friends of likely churners as a way to create "goodwill" around the latter to retain them? The contribution of our paper relies on actively using the social network to design a profitable intervention for the firm as opposed to the previous literature that only used the social network to find peer effects a posteriori. We call this new strategy, in which the friends of likely churners are also contacted by the firm, *socially based proactive churn management*. This strategy proposes a "group-centric" approach to manage churn as traditional proactive churn management is usually focused on targeting consumers independently.

We collaborate with a major telecommunications provider to design, implement, and analyze outcomes of a randomized control trial at the household level. We use data from pay-TV subscriptions to develop a model to predict likely churners and data from call detailed records (CDRs) to draw a social graph across households. On a monthly basis, and during eight consecutive months, we select a random set of likely churners and their friends and allocate them randomly across four different experimental conditions. In particular, we randomly and independently select whether both the former and the latter are listed to be called by a firm's call center. The goal of these calls is to identify likely churners and extend them retention deals to demote them from churning.

We find that, in our setting, traditional proactive churn management decreases the churn rate of likely churners by 1.9 percentage points ($p < 0.01$), from a baseline of 17.2%. The latter is the churn rate observed with reactive retention only. We also find that socially based proactive churn management decreases this statistic by an additional 1.3 percentage points ($p < 0.05$) and increases customer lifetime value relative to traditional proactive churn management, thus improving the firm's bottom line. In addition, we also find no significant change in the churn rate of the friends of likely churners across all our treatment conditions. Our results show that, in our setting, likely churners receive a signal from their friends that lowers their likelihood of churn, which the firm can use to its benefit by targeting consumers along with their friends. This signal may trigger mechanisms akin to conformity and financial comparisons, which are likely to explain the results we observe in our setting. The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the context of our study, and Section 4 explains our experiment in detail. Section 5 shows our results, and Section 6 concludes.

2. Relevant Background

Customer retention has been a central issue in marketing research since the late 1990s. The early studies focused on identifying the drivers of consumer churn and highlighted that customer demographics, such as age, gender and tenure, satisfaction, and perception of fairness, affect the length of stay (e.g., Bolton 1998, Bolton and Lemon 1999). Customer retention has been studied in many different contexts, such as loyalty programs, switching costs, customer self-service channels, pricing policies and advertising expenditure, and management of firm–customer interactions (Reinartz and Kumar 2003, Venkatesan and Kumar 2004, Reinartz et al. 2005). In general, these studies show that the drivers of customer churn are similar across industries and over time. Customer retention has also become a fundamental concern for practitioners because it has been directly linked to firm profitability (Anderson et al. 1994, Rust et al. 2004, Villanueva et al. 2008). Even small increases in retention rates have been shown to yield significant increases in profits (Reichheld and Sasser 1990, Reichheld 2003) because existing consumers tend to be more loyal and generate more revenue (Reichheld and Sasser 1990, Reichheld 2003).

Firms pursue two main approaches to manage customer churn (Winer 2001), namely *reactive churn management*, whereby they wait for consumers to signal their intention to leave and at that time they try to avoid so by offering them aggressive retention deals, and *proactive churn management*, whereby firms try to contact likely churners early to extend them deals to retain them. Proactive churn management may yield higher profits because firms reach consumers at a point in time at which they are cheaper to retain, for example, before contracts expire when consumers have not yet surveyed the market to learn about alternatives. However, the firm needs to identify customers at risk to implement proactive churn management. In particular, the firm needs to reach true churners to avoid losing too much profit with false positives. Therefore, proactive churn management typically starts by identifying likely churners, which has been an exercise that attracted significant research effort in the churn management literature. Neslin et al. (2006) and Lemmens and Croux (2006) were among the first to study data-intensive algorithms to predict churn. Please refer to Ascarza et al. (2017b) for a detailed review of more recent papers on this topic.

The traditional approach to proactive churn management suggests that firms should target individuals with high probability of churn (Blattberg et al. 2008, p. 632). However, the literature provides mixed results in this respect. In the context of pay-TV, Burez and Van den Poel (2007) find a positive effect of proactive churn management on profit. The authors study churn using data from a company that experiences a churn rate of 15%/year, select the top 30% likely churners, and gift them with an invitation to a unique event or free movie tickets or simply ask them to fill in a satisfaction survey. All treatment conditions lead to significant lower churn rate (reductions between 3% and 5% from the aforementioned statistic) with the latter condition being the most efficient in terms of profit to the firm given its low implementation cost (essentially, not extending offers to consumers). In contrast, Ascarza et al. (2016) study churn in a market for prepaid mobile service—experiencing a 6% average churn rate per quarter—and find a negative effect of proactive churn management. The authors select users predicted to benefit from upgrades in their tariff plan and offer a random subset of them a $15 credit for a period of three months, conditional on them upgrading their tariff plan. They find that the churn rate across treated consumers increases to 10% per quarter. The authors provide additional evidence showing that the intervention might have reduced the customers' inertia to change and increased the saliency of usage, potentially leading some customers to search for services from competitors that could better fit their calling needs.

These studies pertain to very different contexts. The former looks at a market in which consumers become locked in before they can churn without paying a financial penalty. The latter looks at a prepaid service from which consumers could churn by simply winding down their account balance. These differences alone may account for the different churn rates observed in these markets, the differences in the observed behavior of consumers, and the differences in the mechanisms that led to such behavior, but they highlight that the question of who to target is far from trivial. More recently, a number of studies propose to choose targets based on their expected profitability (Lemmens and Gupta 2017) or on their likelihood of changing behavior if targeted, also known as uplift (Ascarza 2017), rather than on their absolute level of risk because such approaches are likely to better maximize client lifetime value (Gupta et al. 2004, Blattberg et al. 2008). The argument used in these papers is that optimizing targeting algorithms only to identify the individuals who are most likely to churn may end up targeting less profitable ones, that is, those who would always stay with the firm, those who never stay with the firm, or those who may be induced to leave because of targeting.

All studies mentioned before assume that consumers make independent decisions about which services to abandon. In these studies, consumers are described as independent agents who make decisions based on their individual experience with the services to which they subscribe, their personal profile, and the marketing they receive (Peres et al. 2010, Solomon 2014). Accordingly, marketing campaigns have been largely designed to target consumers one by one. However, in recent times, researchers began collecting evidence showing that social networks play an important role in many consumer decisions, including churn. Nitzan and Libai (2011) ran an observational study over one million customers of a cellular company and found that exposure to a churner is associated with an increase of 80% on the hazard of churn. The authors found this result after controlling for a number of individual-level covariates that proxy social, personal, and purchase-related traits, which lessen concerns with endogeneity. They also discuss how this effect is economically large by comparing it with those found in the literature on adoption. In addition, they also found that the effect of social influence depends on the number of ties, tie strength, customer loyalty, and that it decays exponentially over time. Highly connected customers are more affected by neighbor defection, and loyal customers are less so. This study provides a thorough analysis of how communication across consumers affects churn and shows why studying the relationship between peer effects and churn is paramount for managers in the field.

Ascarza et al. (2017a) complements our knowledge of peer influence on churn. The authors report the existence of spillovers in churn behavior by looking at the outcomes of a randomized field experiment in prepaid mobile. They found that proactively targeting likely churners has a positive effect not only on the targeted individuals, but also on their friends. The authors identified customers at risk as those who would have their accounts suspended if they did not top up their balance in one week. They sampled 961 such customers and treated 67% of them, selected at random, with a credit incentive that could be used to place calls. The authors found that their intervention increased usage by 35% on the targeted consumers and 10% on the neighbors of the targeted consumers. They also found that the friends of targeted consumers churn less, a spillover effect that they attribute to the nature of the product studied. Their setting is one with explicit network externalities, whereby consumers can place an unlimited number of in-network calls and use their balance to pay for out-of-network and international calls. Therefore, in their setting, peer influence was likely to be triggered by this economic principle.

Our paper contributes to both these lines of research by testing whether peer effects can be exploited to improve the performance of proactive churn management. We propose that firms can actively use the social network to design profitable interventions as opposed to the previous literature that only used the social network to find peer effects a posteriori. In particular, we test whether targeting likely churners and their friends in the same proactive retention campaign with the same menu of nonreferral retention deals reduces churn. Unlike Nitzan and Libai (2011) and Ascarza et al. (2017a), we study a context in which the way consumers use the service does not involve explicit network externalities, and thus, it is unclear whether peer effects would arise in such a setting and, if so, whether they would be economically significant. Finally, and in line with the suggestions in Reichheld and Sasser (1990), Berger and Nasr (1998), Jain and Singh (2002), and Rust et al. (2004), we use customer lifetime value to compare the performance of our strategy with that of traditional proactive churn management, thus measuring its effect on the firm's bottom line.

3. Context and Historical Data Sources

We study whether the peer effects in churn decisions discussed in Nitzan and Libai (2011) and in Ascarza et al. (2017a) in cell phone markets may also arise in the context of triple-play markets without explicit network externalities and, if so, whether firms can use them to improve churn management. Therefore, our setting is closer in nature to that studied in Burez and Van den Poel (2007), but these authors did not analyze peer effects. The relevance of studying triple-play markets, as opposed to cell phone service and pay-TV service separately, stems from the fact that triple play is now becoming the dominant mode of consumption for telecommunications services. According to Digital TV Research, global triple-play subscriptions will reach 400 million by the end of 2017, up by nearly 300 million from the end of 2011. In addition, firms experience churn rates as high as 1% per month in these markets (Green 2016).

We collaborate with a large multinational telecommunications provider, hereinafter called TELCO. In the geography we analyze, TELCO serves more than one million households with TV, Internet, and telephony. In this setting, households become locked in when they contract service. We have anonymized data from TELCO between January 2013 and March 2015 and then for the month of January 2016. These data contain monthly snapshots of all TELCO products subscribed to by all TELCO households. We also know each household's monthly bill and the price charged by competitors for similar services in the same region. In April 2014, the average monthly bill at TELCO was \$54.70/month. Therefore, choosing whether to stay with TELCO or churn is a decision that has significant financial implications for consumers in our setting.

We also have anonymized call detailed records for all landline calls served by TELCO between July 2012 and June 2013. This data set contains more than 600 million records. We use these data to define an undirected graph of communications across households. We build this graph by matching all anonymized phone numbers to their corresponding anonymized pay-TV accounts. We discard all CDRs in which one of the calling parties is a number with no counterpart in the anonymized pay-TV database. An edge between two households is included in this graph if all of the following conditions are met: (1) there are two or more calls between them, (2) at least one of the calls took place after 7 pm, (3) at least one of the calls occurred during the weekend, and (4) there are calls between them in at least two months. Our criteria to add edges to this graph ensure that households contacted each other over landlines, after normal working hours, on weekends, and more than once. Thus, edges in our graph proxy real proximity between households and possibly family ties. The resulting social graph contains 1.2 million nodes and 2.63 million edges. The average and the median degree are 4.3 and 3, respectively. The household in the 99th percentile is connected to 20 households.

4. Our Experiment

The best way to determine whether proactive churn management may help TELCO retain customers is to implement a randomized control trial in which a random set of likely churners are listed to be called by the firm and another random set of likely churners is held out for control purposes. This setup allows us to control for all unobserved effects that may lead likely churners to churn and that could otherwise be related to proactive churn management had the firm selectively chosen households to call. In addition, we are also interested in learning whether the social network can be used to increase the efficiency of proactive churn management by leveraging potential peer effects. However, many unobserved factors that lead households to churn from TELCO are likely to be correlated among households connected in the social graph because of homophily. In fact, it is well known that empirically measuring the effect of peer influence is a hard task because of the confounding effects introduced by unobserved covariates that simultaneously drive friendship and behavior (Manski 1993, McPherson et al. 2001, Shalizi and Thomas 2011). We use a carefully designed randomized experiment to measure peer effects in our setting as described in the following. Our experiment is inspired by what has been done in the previous literature in other settings, such as Facebook (Aral and Walker

2011), news aggregators (Muchnik et al. 2013), and music recommendations (Bapna and Umyarov 2015).

4.1. Initial Setup

The initial setup of our experiment took place in the end of April 2014 and consisted of developing a model to predict churn. Using the monthly panel of households served by TELCO, we developed a model that maps a vector of household characteristics to likelihood of churn. This model was constructed using state-of-the-art data-mining algorithms for classification tasks. Its details, training parameters, cross-validation, and performance metrics are all presented in Online Appendix B. This churn prediction model shows that tenure, an active lock-in period, the amount billed, the age of the contract holder, and how much the household is off price are among the most important predictors of churn at TELCO. How much the household is off price is measured by the difference between the monthly bill and the lowest monthly bill offered by competitors for a similar bundle of services in the same region. Building this churn prediction model implements step one in the framework proposed by Blattberg et al. (2008) to measure the effect of proactive churn management. This churn prediction model allows us to focus our experiment on likely churners. As a consequence, our results generalize only to TELCO's likely churners, which is the subpopulation of interest for churn management purposes.

In addition, and also in April of 2014, we identified the ego network of each household in our social graph. In social network analysis, the ego network of a node in a social graph is the subgraph containing that node, called the ego; all nodes connected directly to it, called alters; and all the edges between them (Wasserman 1994). Panel (1) in Figure 1 shows an example of an ego network. Finally, and also in April 2014, we also determined the sample size required to identify an effect that would render proactive churn management profitable on egos. Finding an effect that does not generate profit would be uninteresting from an economic point of view. Online Appendix C provides the details of the calculations that we performed for this purpose, which allowed us to determine that our experiment should run for at least eight consecutive months.

4.2. Monthly Operations

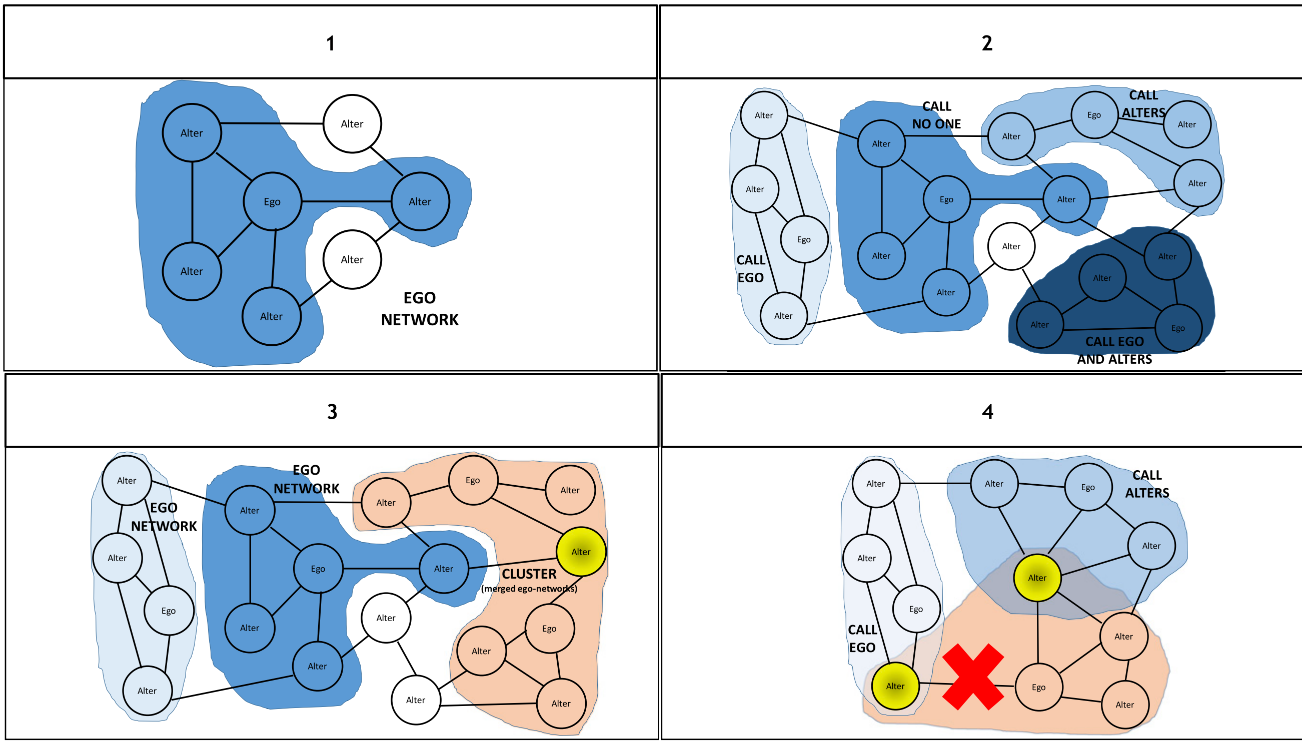
Every month, starting from May 2014, TELCO provided us access to a data set with a collection of covariates that allowed us to determine whether a household initiates churn. Households can initiate churn through several channels: by phone, mail, email, or visiting a TELCO store. A household that signals its intention to churn using any of these channels is marked as so in our data set. Every month, we run our churn prediction model for households that did not initiate churn in the previous three months. TELCO refers to this period as "mourning." Its purpose is to ensure that households do not receive multiple contacts when parallel negotiations may already be underway. We note that our churn prediction model was retrained twice during our experiment, namely in May and October 2014, when TELCO refreshed our data sets on household-level covariates. Table 1 shows a timeline of our experiment and which data were used when and for what purpose.

Each month during the experiment, we randomly placed the ego network of each top (as defined in Online Appendix C) likely churner in one of four conditions: *Call No One*—the ego and its alters are all listed not to be called by the firm; *Call Ego*—the ego is listed to be called by the firm and all its alters are listed not to be called by the firm; *Call Alter*—the ego is listed not to be called by the firm and all its alters are listed to be called by the firm; and *Call Ego and Alter*—both the ego and all its alters are listed to be called by the firm. We choose to list either no alter or all alters to be called by the firm to maximize our chance of finding an effect of peer influence. If there is no effect when all alters are listed to be called by the firm, then it is very unlikely that an effect arises when fewer alters are listed to be called.

Panel (2) in Figure 1 shows an example of a network in which each ego network is randomly placed in one of these four different conditions. This panel in this figure shows how considering ego networks introduces separation between egos in different treatment conditions, which reduces the likelihood of violating the stable unit treatment value assumption (SUTVA) (Rosenbaum 2007, Wooldridge 2010). Violating SUTVA would hamper our ability to identify causal treatment effects resulting from interference across conditions. This is a common concern in network settings (e.g., Manski 1993, McPherson et al. 2001, Shalizi and Thomas 2011, and Eckles et al. 2014). Randomizing treatment assignment to ego networks addresses this concern as suggested in Ugander et al. (2013). Considering ego networks in our setting ensures that egos in different treatment conditions are at least two hops away from each other. Assuming only one-hop peer influence is a common practice in the literature in peer effects (e.g., Aral and Walker 2011, Bapna and Umyarov 2015, and Ugander et al. 2012). In our setting, only 2.8% of the egos are connected to egos in a different cluster by two hops. Moreover, less than 2% of the egos are connected by two hops to egos in clusters with different treatment conditions. Furthermore, we find no evidence of peer influence over two hops in our case (results available upon request).

Complex situations arise when ego networks overlap, such as in panel (3) of Figure 1, in which two egos share one alter. To ensure consistency, in this case, we merge the two ego networks into a larger cluster, assign

Figure 1. (Color online) Cluster Setup, Randomized Assignment, and Conflict Resolution



Notes. Panel 1: example of ego-network. Panel 2: example of random assignment of treatment conditions to ego-networks. Panel 3: example of merging ego-networks that share alters. Panel 4: example of dynamic inconsistency leading to discard households from the analysis.

the same condition to both egos in this cluster, and assign the same condition to all alters in the cluster. Therefore, alters in this cluster will either all be listed to be called by the firm or all be listed not to be called by the firm. In other words, once clusters are formed (and, without overlap, clusters are just ego networks), each cluster is randomly placed in one of the four treatment conditions referred to earlier. Finally, we note that our experiment took place over several months. Therefore, when we select an ego to be included in the experiment, it may be the case that it is connected to households that were already assigned to different treatment conditions in previous months. According to our experimental design, this would require us to merge clusters that were assigned to different treatment conditions, such as in panel (4) in Figure 1. We circumvent this limitation of our experimental design by discarding from our analysis all households in the new cluster. This limitation led us to discard only 1% of the households in our sample.

After the experimental procedure described previously, the monthly random assignment of clusters to the four treatment conditions resulted in lists of households to be called by the firm and lists of households not to be called by the firm that we provided to TELCO's call center every month. We note that, in our setting, reactive retention is modeled by the condition *Call No One*, under which households still churn organically by calling the firm. Our other three treatment conditions embody an element of proactive churn management given that the firm is the party initiating contact. We followed households for a period of 120 days after treatment assignment and again in January 2016, that is, one year after our experiment ended. We note that from historical data, 95% of true positives listed by our predictive model request to disconnect their service (that is, enter the reactive retention) in the first 120 days after being identified by our model.

4.3. Descriptive Statistics and Balance Across Treatment Conditions

Figure 2 plots the number of clusters in each treatment condition. There are many more clusters in the *Call Ego* condition because TELCO required us to focus its call center efforts on likely churners. In fact, TELCO increased the capacity of the call center allocated to our experiment one month after it started and added more slots to call likely churners. This did not raise problems to our experiment because, overall, we still assigned enough households to each treatment condition to identify the desired effects. Table 2 provides precise definitions for all covariates used throughout our paper. Tables 3–5 provide descriptive statistics for the most important covariates that, in our setting, shape consumer behavior—churn score, monthly bill, and lock-in period—for all egos, all alters, and all clusters in

Table 1. Experimental Timeline Indicating the Calibration of Our Churn Prediction Model and the Data Used to Select Households for the Experiment

Churn prediction model	
Training and calibration	Used to select households
Trained in April 2014 using data up to Dec. 2013 To predict churn Jan. 15 to Feb. 15, 2014	
	Used in May 2014 with data up to April 2014 To predict churn June 15 to July 15, 2014 Used to select first wave of households on June 1, 2014
Retrained in June 2014 using data up to Feb. 2014 To predict churn March 15 to April 15, 2014	
	Used in June 2014 with data up to May 2014 To predict churn July 15 to Aug. 15, 2014 Used to select second wave of households on July 1, 2014 Used in July 2014 with data up to June 2014 To predict churn Aug. 15 to Sept. 15, 2014 Used to select third wave of households on Aug. 1, 2014 Used in Aug. 2014 with data up to July 2014 To predict churn Sept. 15 to Oct. 15, 2014 Used to select fourth wave of households on Sept. 1, 2014 Used in Sept. 2014 with data up to Aug. 2014 To predict churn Oct. 15 to Nov. 15, 2014 Used to select fifth wave of households on Oct. 1, 2014
Retrained in Oct. 2014 using data up to May 2014 To predict churn June 15 to July 15, 2014	
	Used in Oct. 2014 with data up to Sept. 2014 To predict churn Nov. 15 to Dec. 15, 2014 Used to select sixth wave of households on Nov. 1, 2014 Used in Nov. 2014 with data up to Oct. 2014 To predict churn Dec. 15, 2014, to Jan. 15, 2015 Used to select seventh wave of households on Dec. 1, 2014 Used in Dec. 2014 with data up to Nov. 2014 To predict churn Jan. 15 to Feb. 15, 2015 Used to select eighth wave of households on Jan. 1, 2015

our experiment, respectively. The average degree of egos and alters in our experiment is 1.84 and 6.36, respectively. Their average churn scores are 0.71 and 0.24, respectively. As expected, the churn score of egos is much higher in our setting. The average monthly bill and lock-in period for egos 30 days before treatment assignment were \$56.20 and 31.1 days, respectively. These statistics are \$54.70 and 132.2 for alters, respectively. Therefore, in our setting, alters are much less inclined to churn because they enjoy lower monthly bills and face longer lock-in periods. Online Appendix D provides additional evidence of balance in these covariates across treatment conditions on a monthly basis.

4.4. Offers, Potential Outcomes, and Compliance Levels

Figure 3 describes the decision stages and possible outcomes for households included in the experiment. At the start of each month, lists of households to be included in the experiment were sent to the call center. Some of these households, selected at random as described in Section 4.2, were marked to be called by the call center dialer. The remaining households were marked not to be called, which helped ensure compliance with the hold-out conditions. The latter households do not change their service conditions unless they call the firm to leave, in which case they enter reactive retention. Call center operators were not told which households were egos nor alters. They did not know the churn scores from our churn prediction model, and they were not told that some households in these lists were connected in the social graph. The operations of TELCO's call center are based on automatic dialers that randomize the order and time at which households are contacted and recontacted when previous calls fail. In short, in our setting, there is no selection bias in terms of how calls were attempted. Yet a number of unknown reasons may result in missed calls. It is still up to each household to pick up the phone from TELCO. This introduces a first layer of selection in our experiment. The top left and top right panels in Figure 4 show that egos listed to be called by the firm were reached 51% of the time and that alters listed to be called by the firm were reached 57% of the time.

When a call is established, the call center operator tries to assess whether the household reached is likely

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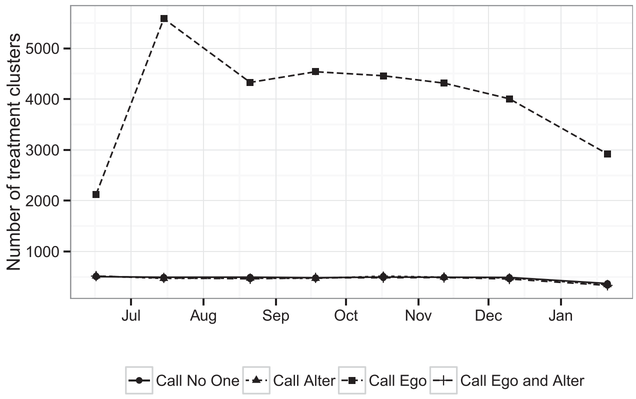
Figure 2. Number of Clusters per Treatment Condition over Time During the Experiment



to churn. A satisfaction survey is used to do so. All call center operators follow the same survey, that is, the same questions in the same order were asked during each and every call made. If the call center operator determines that the household is unlikely to churn the operator explains why the current contract and service fit the needs of that household and wraps up the call with no offer, and thus, there is no change in the household's contractual conditions. If, on the other hand, the call center operator determines that the household is likely to churn, then a deal is offered to try to retain the household. A menu with three different levels of offers was available to call center operators for this purpose: (i) offer A—reduced quality of service (such as fewer TV channels or lower Internet speed) for a lower price, (ii) offer B—a discount of $3 in the monthly bill corresponding to the free rental of the set-top box, and (iii) offer C—a $7 discount in the monthly bill. This menu of offers was the same for each and every call made during our experiment. Yet call center operators were free to negotiate which offer to extend on a case-by-case basis but asked to try to retain the consumer at the least possible cost for the firm. In fact, call center operators were paid more if they were able to increase the household's contractual commitments and particularly high cash bonuses were paid when they were able to convince households to increase their monthly bill (which is extremely rare). The freedom given to call center operators to negotiate as best as possible with consumers introduces a second layer of selection in our experiment. The bottom left and bottom right panels in Figure 4 show that egos listed to be called by the firm were given a retention offer 34% of the time. Alters listed to be called by the firm received such offers 30% of the time. Obtaining an offer is conditional on getting a phone call from the call center. Therefore, roughly two thirds of the households that

Table 2. Definition of Variables Used in the Paper

Name	Type	Description
Call No One	Dummy variable	= 1 for households in clusters assigned to the Call No One condition
Call Alter	Dummy variable	= 1 for households in clusters assigned to the Call Alter condition
Call Ego	Dummy variable	= 1 for households in clusters assigned to the Call Ego condition
Call Ego and Alter	Dummy variable	= 1 for households in clusters assigned to the Call Ego and Alter condition
Churn Score	Continuous variable	Churn score calculated by the predictive churn model
Reactive retention After 120 Days	Dummy variable	= 1 for households that request to churn within 120 days after treatment assignment
Churn by Jan. 2016	Dummy variable	= 1 for households that churned by January 2016
Lock-in Period	Continuous variable	Number of days to current contact expiry
Monthly Bill	Continuous variable	Monthly bill associated with all telecommunication services (= 0 for households who churn)
Gets Call	Dummy variable	= 1 for households that got a call from the call center
Fraction of Friends Get Call	Continuous variable	Proportion of household's friends that got a call from the call center
Gets Offer	Dummy variable	= 1 for households that got a retention offer from the call center
Fraction of Friends Get Offer	Continuous variable	Proportion of household's friends that got an offer from the call center
Offer A	Dummy variable	= 1 for households that got a retention offer A from the call center
Offer B	Dummy variable	= 1 for households that got a retention offer B from the call center
Offer C	Dummy variable	= 1 for households that got a retention offer C from the call center

Table 3. Descriptive Statistics for Egos in the Experiment per Treatment Condition

Treatment	Variable	Observations (egos)	Average	Standard deviation
Call No One	*N. alters*	3,996	1.890	1.067
Call Alter	*N. alters*	3,895	1.890	1.080
Call Ego	*N. alters*	33,312	1.830	1.045
Call Ego and Alter	*N. alters*	3,820	1.849	1.018
Call No One	*Churn score*	3,996	0.689	0.274
Call Alter	*Churn score*	3,895	0.689	0.271
Call Ego	*Churn score*	33,312	0.715	0.276
Call Ego and Alter	*Churn score*	3,820	0.691	0.273
Call No One	*Monthly bill*	3,996	55.722	13.951
Call Alter	*Monthly bill*	3,895	55.824	13.846
Call Ego	*Monthly bill*	33,312	56.300	13.593
Call Ego and Alter	*Monthly bill*	3,820	55.637	14.001
Call No One	*Lock-in period*	3,996	30.801	77.817
Call Alter	*Lock-in period*	3,895	33.937	87.800
Call Ego	*Lock-in period*	33,312	30.814	79.083
Call Ego and Alter	*Lock-in period*	3,820	30.863	80.765

Note. Monthly bill and lock-in period computed 30 days before treatment assignment.

were reached during our experiment were given a retention offer. Online Appendix A provides additional descriptive statistics about which offers were accepted and not by households in the experiment. When an offer is made, the household decides to accept or reject it on the spot. If the household accepts an offer from the call center operator, then its conditions are updated and the call ends. However, the consumer has 15 days to call back and ask to revert to the previous conditions. If this is the case, then the consumer enters reactive retention, and the firm will try to retain the consumer. If the household rejects the offer from the call center operator, no change is made to the household's conditions and the call ends. However, a consumer who rejects such an offer also has 15 days to call back to accept it. All offers extended by TELCO under this type of campaign are registered in TELCO's information system, and the company typically honors offers that it had previously extended to consumers. If this happens, the conditions of that household change. Finally, we note that whenever households are on the phone with a call center agent, they may ask for the service to be disconnected. In that case, consumers are routed toward the reactive retention team and the firm initiates all churn-related procedures.

5. Results

In this section, we measure the effect of proactive churn management in our setting by comparing the behavior of egos in the *Call No One* condition and in the *Call Ego* condition. We also measure the effect of socially based proactive churn management by comparing the behavior of egos in the *Call Ego* condition and in the *Call Ego and Alter* condition. All these results measure the

Table 4. Descriptive Statistics for Alters in the Experiment per Treatment Condition

Treatment	Variable	Observations (alters)	Average	Standard deviation
Call No One	*N. alters*	6,545	7.677	32.444
Call Alter	*N. alters*	6,235	6.150	9.633
Call Ego	*N. alters*	55,925	6.272	9.093
Call Ego and Alter	*N. alters*	6,043	5.923	5.561
Call No One	*Churn score*	6,545	0.230	0.268
Call Alter	*Churn score*	6,235	0.222	0.262
Call Ego	*Churn score*	55,925	0.240	0.275
Call Ego and Alter	*Churn score*	6,043	0.224	0.261
Call No One	*Monthly bill*	6,545	54.420	23.603
Call Alter	*Monthly bill*	6,235	54.846	23.513
Call Ego	*Monthly Bill*	55,925	54.761	24.040
Call Ego and Alter	*Monthly bill*	6,043	54.704	23.624
Call No One	*Lock-in period*	6,545	128.649	232.783
Call Alter	*Lock-in period*	6,235	131.182	234.552
Call Ego	*Lock-in period*	55,925	132.666	235.551
Call Ego and Alter	*Lock-in period*	6,043	132.708	234.636

Note. Monthly bill and lock-in period computed 30 days before treatment assignment.

Table 5. Descriptive Statistics for Clusters in the Experiment per Treatment Condition

Treatment	Variable	Observations (n clusters)	Average	Standard deviation
Call No One	*N. egos*	3,831	1.043	0.250
Call Alter	*N. egos*	3,774	1.032	0.192
Call Ego	*N. egos*	32,270	1.032	0.197
Call Ego and Alter	*N. egos*	3,707	1.030	0.180
Call No One	*N. alters*	3,831	1.972	1.284
Call Alter	*N. alters*	3,774	1.950	1.237
Call Ego	*N. alters*	32,270	1.889	1.178
Call Ego and Alter	*N. alters*	3,707	1.905	1.128
Call No One	*Cluster size*	3,831	3.015	1.433
Call Alter	*Cluster size*	3,774	2.983	1.337
Call Ego	*Cluster size*	32,270	2.921	1.277
Call Ego and Alter	*Cluster size*	3,707	2.936	1.210

impact of our randomized assignment of households to treatment conditions before any selection occurs. This yields the effect of the intention-to-treat households proactively across the population of likely churners at TELCO, which provides causal evidence of the effect of listing them to call. Online Appendix F provides estimates for the effect of treatment across the subpopulation of egos that pick up the call from the firm. We also note that the probability of treatment assignment changed from month to month during our experiment. For example, the number of slots that were allocated to our experiment changed every month and in particular in June 2014. This means that the results that we present are precision-weighted averages of monthly effects.

5.1. Effect of Churn Management on Entering Retention and Churn

We start by pooling all observations together to find whether there is some indication that our treatments yielded some effect. Figure 5 illustrates the results obtained for egos and alters in the top and bottom panels, respectively. The vertical axes on the left panels measure entry into reactive retention 120 days after treatment assignment. The vertical axes on the right panels measure churn in January 2016. The top panels show preliminary evidence that listing only alters to call does not change the likelihood at which egos enter reactive retention or churn. However, listing egos to call reduces their likelihood of doing so, and listing both egos and alters to call seems to yield even a larger effect. The bottom panels show that none of our treatments affected the likelihood at which alters enter reactive retention or churn. Figure 6 illustrates what happens to monthly bills and to lock-in periods during our experiments. The top panels are for egos, and the bottom panels are for alters. The vertical axes on the left panels measure changes in monthly bills. The vertical axes on the right panels measure changes in lock-in periods. The left top panel shows that listing only alters to call does not change the monthly bills of egos. Listing egos to call reduces their monthly bills. Listing their alters to call reduces the monthly bills of egos by a similar amount on average. The left bottom panel shows that listing egos to call does not change the monthly bill of alters. Listing alters to call reduces their monthly bills. The panels on the right show similar results for lock-in periods.

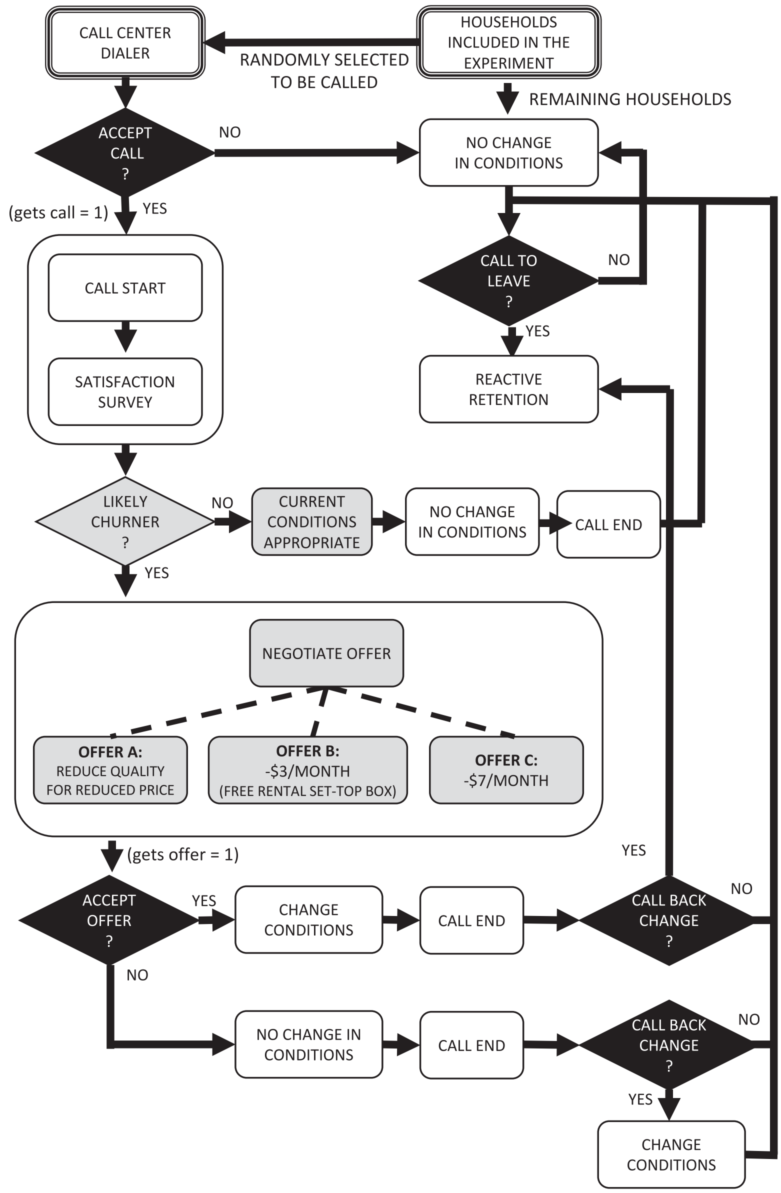
We estimate the magnitude of the causal effects of our treatments using the following model:

$$Y_j = \zeta_0 + churn\_score_j\alpha_1 + \mathbf{treatment}_j\boldsymbol{\alpha_2} + \theta_t + \epsilon_j \quad (1)$$

where j is a household in our experiment, Y_j represents either entering reactive retention 120 days after treatment assignment or churn in January 2016, $\mathbf{treatment}_j$ is a vector of indicators for our treatment conditions, and $\boldsymbol{\alpha_2}$ is a vector of parameters indicating the corresponding levels of our dependent variable. Differences among these parameters readily measure the effect of proactive churn management and of socially based proactive churn management on our dependent variable. We use a linear probability model (LPM) to estimate this equation. LPM is appropriate to identify the average causal effect of treatment assignment in randomized experiments with binary outcomes when the covariates of interest are sparse and discrete as in our case (Angrist 1991, Angrist et al. 1996, Angrist 2001). For completeness, we present results using probit in Online Appendix E, which are both qualitatively and quantitatively similar to the ones discussed in the following.

Table 6 shows the effect of treatment assignment on egos during our experiment. Columns (1) and (3) show that listing alters to call does not change the likelihood at which egos enter reactive retention or churn. However, listing egos to call reduces the former by 1.7 percentage points, from a baseline of 20.7%, and reduces the latter by 1.9 percentage points, from a baseline of 17.2%. Columns (2) and (4) show that listing alters to call in addition to listing egos to call reduces the likelihood at which egos enter reactive retention by an additional 1.4 percentage points and the likelihood of churn by an additional 1.3 percentage points. Online Appendix G shows that these effects are not affected by tie strength or by the degree

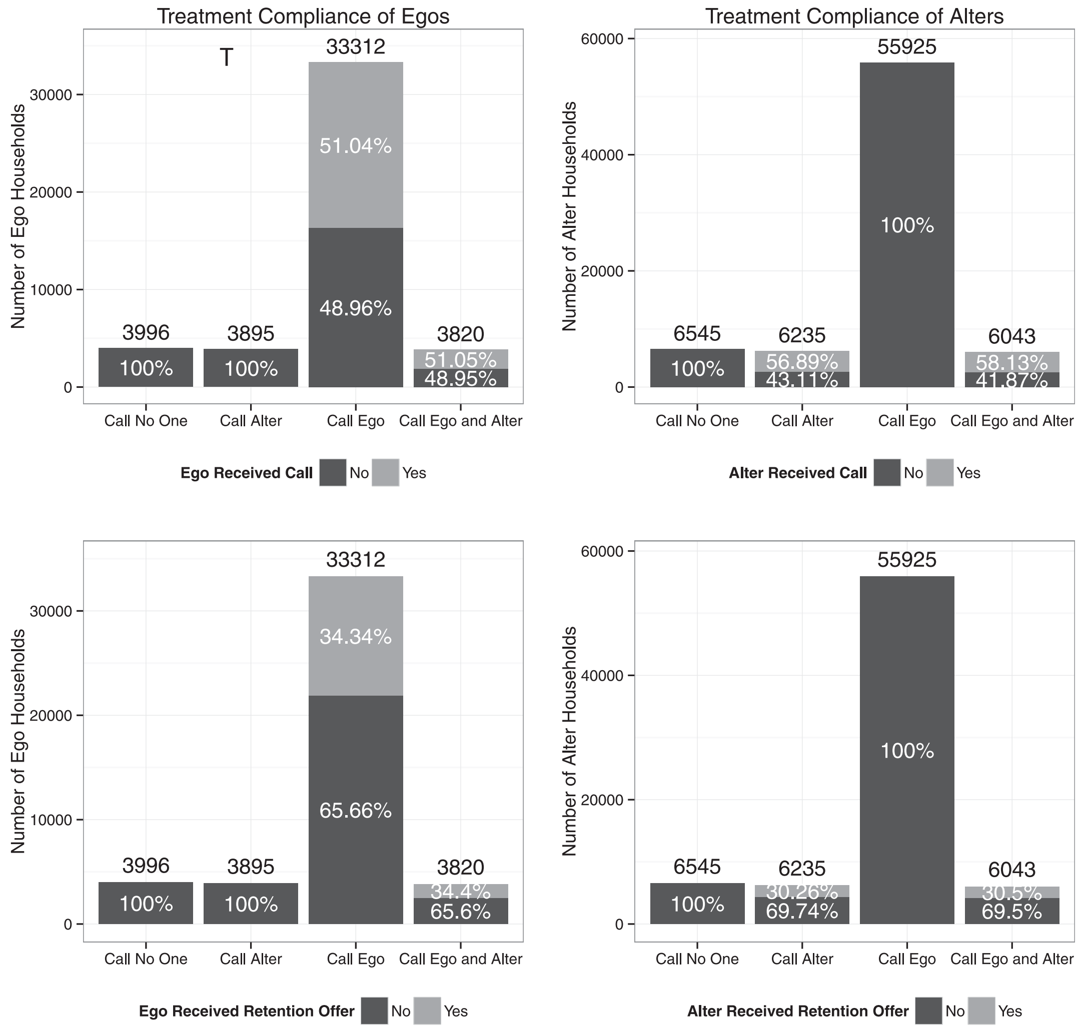
Figure 3. Decision Stages and Possible Outcomes for Households Contacted by the Firm During Our Experiment



centrality of the ego. Instead, in our setting, these effects are moderated by the proportion of alters who pick up the phone from the call center as shown in Online Appendix F. Finally, Table 7 shows results for the case of alters. All treatment conditions yield a similar likelihood of entering reactive retention and a similar churn rate.

Our results show that calling only likely churners does not yield a spillover effect to alters, and that calling only alters does not have a spillover effect to egos. This is different from Ascarza et al. (2017a), in which the authors found evidence of spillover effects. However, they studied a product with explicit network externalities, which, as the authors argue, drives the results that they observed. Our case is different. We analyze a market without explicit network externalities and, in our setting, spillover effects arise only when both parties—the likely churner and the churner's friends—are listed to be called by the firm. This shows that one must be very careful when generalizing spillover effects and that the effects identified in Ascarza et al. (2017a) may not generalize even within the telecommunications industry. More important, our findings show that, in our setting, a signal flows from alters to egos that lowers the likelihood at which the latter enter reactive retention and churn (in January 2016). This follows from the fact that with random assignment egos in the *Call Ego* and in the *Call Ego and Alter* conditions are, on average, similar on everything except for the fact that their alters were also listed to be called by the firm under the latter condition. We cannot identify the channel used to transmit this signal, nor can we be sure of what the signal is because we do not observe the messages exchanged between

Figure 4. Compliance with Treatment Assignment During the Experiment



Note. The left panels show compliance across egos, and the right panels show compliance across alters.

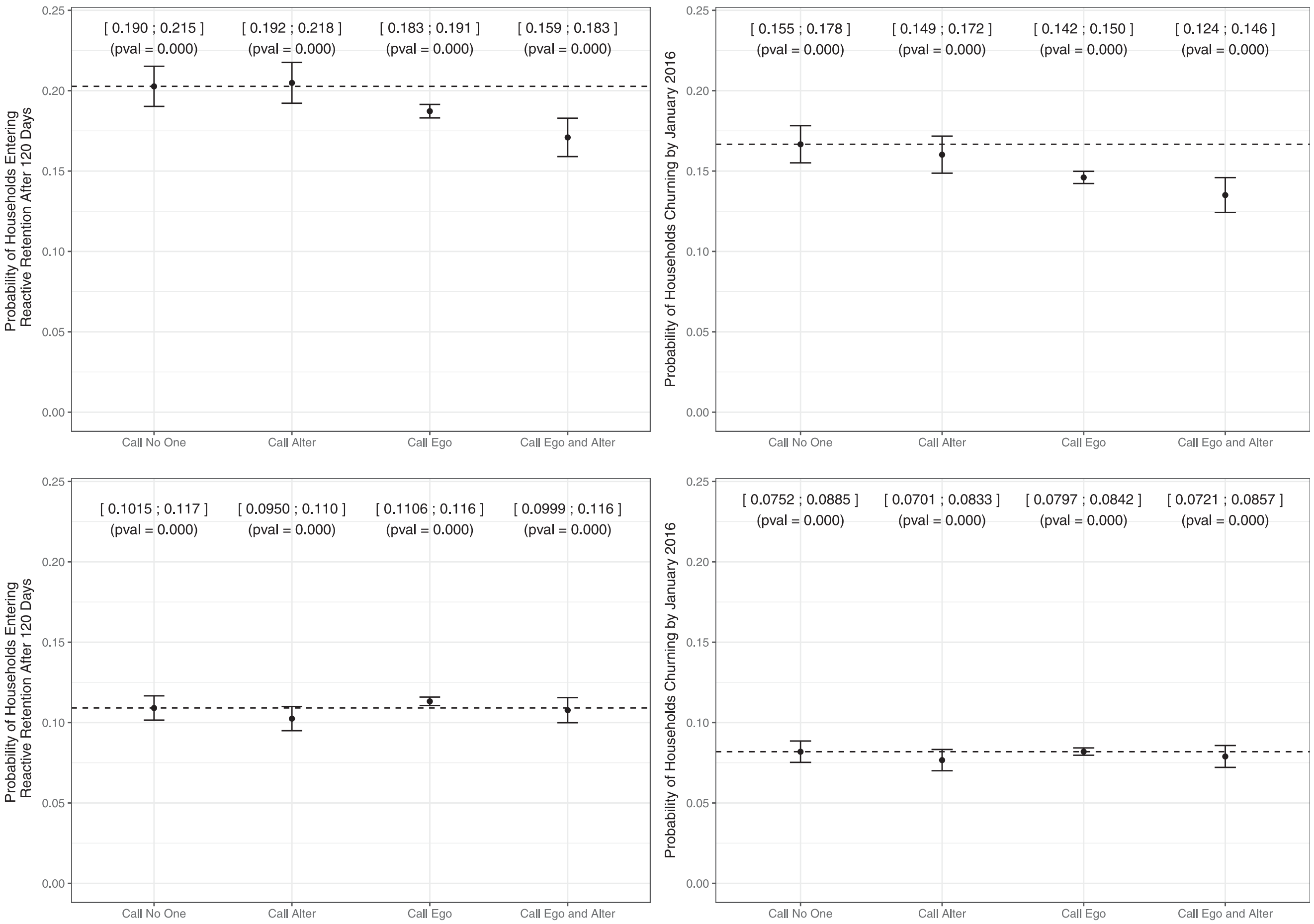
egos and alters. Yet such a signal is certainly present in our setting and is responsible for the effects observed with socially based proactive churn management.

5.2. Mechanisms at Play in Socially Based Proactive Churn Management

Proactive churn management triggers a number of mechanisms that have been already discussed in the prior literature and that may arise in our setting. For example, egos go through a satisfaction survey when they pick up the call from the firm, which may reduce their likelihood of churn. As pointed out by Burez and Van den Poel (2007), satisfaction surveys may lead to positive evaluations that help retain consumers. However, this does not seem to be the case in our setting as explained in detail in Online Appendix H. The egos who accept offers from the firm reduce their monthly bills (from \$59.80/month on average 30 days before being included in the experiment to \$56.20/month on average 30 days after being included in the experiment), which may, just per se, also lower their likelihood of churn. In addition, the offers that egos receive from the firm allow them to align their monthly bills with those of their alters (the average monthly bill of alters is \$55.30/month 30 days before being included in the experiment), which is likely to increase their perception of fairness, thus potentially leading them also to churn less. For example, Bolton (1998) and Bolton and Lemon (1999) provide evidence that the perception of fairness reduces defection in environments in which consumers can easily and meaningfully compare the prices that they are charged with those charged to their friends.

The mechanisms referred to here can be at play in traditional proactive churn management and, thus, may explain the difference in the churn rates that we observe between egos in the *Call No One* and in the *Call Ego* conditions. The advantage of our study is that none of them are likely to play a role in explaining the lower churn rate of egos under socially based proactive churn management. To see this, consider Table 8, which compares

Figure 5. Likelihood of Entering Reactive Retention During the Mourning Period (Left) and Likelihood of Churn by January 2016 (Right) per Treatment Condition

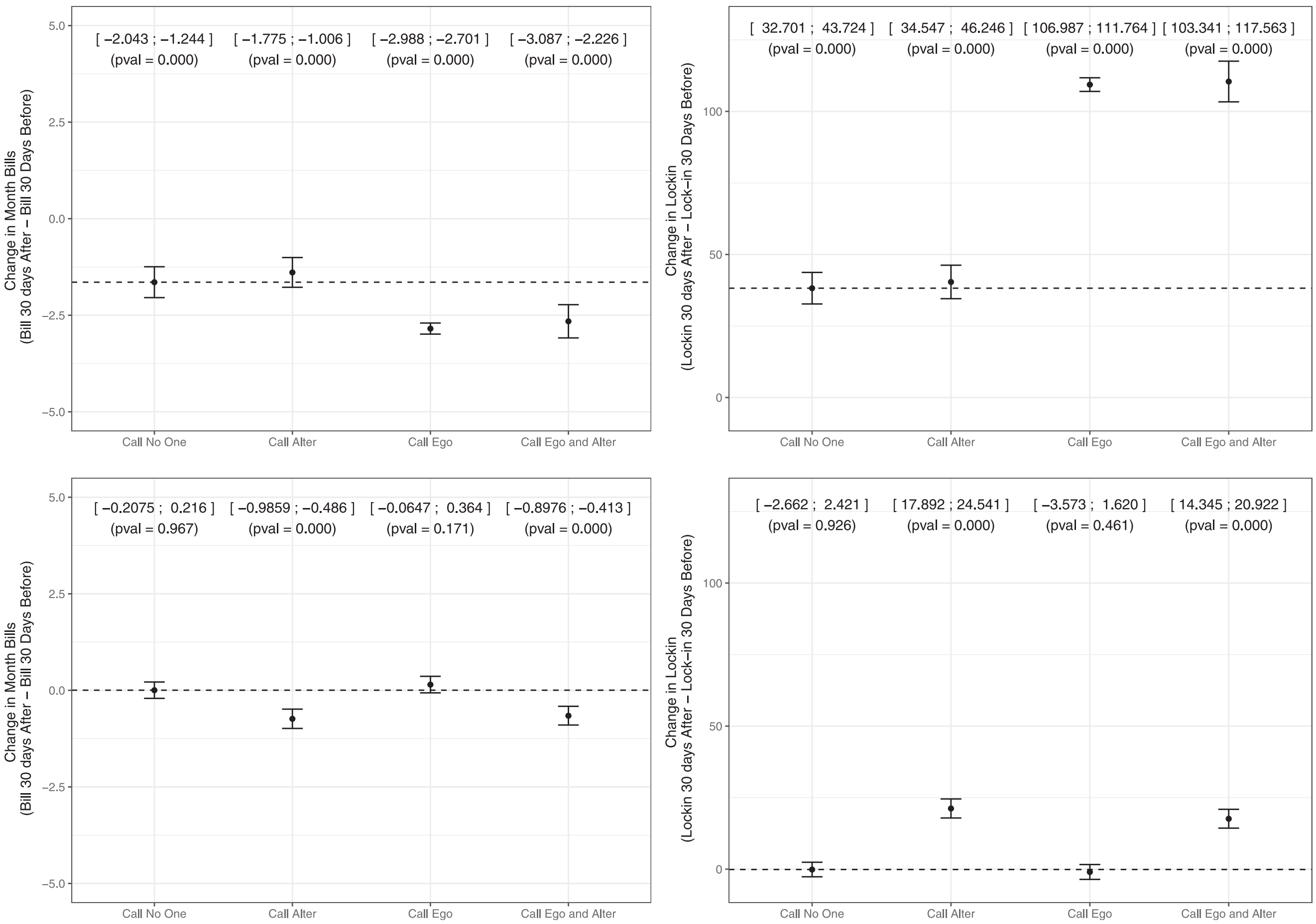


Note. The top panels are for egos, and the bottom panels are for alters.

egos in the *Call Ego* and in the *Call Ego and Alter* conditions. Column (1) shows that egos in these two conditions pick up the phone from the firm at the same rate during our experiment. All egos who pick up the phone from the firm in these conditions go through the same satisfaction survey, that is, the survey included the same questions in the same order for each and every call made by any call center agent during our experiment. Column (2) in this table shows that egos in these two conditions not only pick up the phone from the firm at the same rate, but that they also get offers from the firm at the same rate during the experiment. Columns (3)–(5) in this same table show that they even get the same offers equally often. Therefore, on average, egos in these two conditions have the same opportunities to lower their monthly bills if they accept the offers from the firm (note that even the monthly bill 30 days after treatment assignment for egos that accept offers and remain with the firm is similar, on average, for egos in these two treatment conditions: \$56.20/month under the *Call Ego* condition and \$56.50/month under the *Call Ego and Alter* condition). Furthermore, recall that, also on average, egos in these two conditions have the same monthly bills to begin with (as shown in Table 3) and so do alters (as shown in Table 4). Hence, reductions in the monthly bills of egos are very unlikely to explain the difference in their churn rates across these two conditions. Some alters under the *Call Ego and Alter* condition obtain and accept offers from the firm (which is unlikely under the *Call Ego* condition when alters are not listed to be called by the firm). Therefore, with respect to financial comparisons, if anything, the gaps in monthly bills between egos and alters reduce slightly less under socially based proactive churn management, which would likely lead to a higher churn rate across egos under the *Call Ego and Alter* condition, which is not what we observe in our setting.

This discussion provides evidence that other mechanisms must be at play in the case of socially based proactive churn management. The local average treatment effects reported in Online Appendix F show that the effect of socially based proactive churn management is associated with the alters who pick up the phone from the firm. However, in our setup, we are unable to split this effect into the one associated with

Figure 6. Change in the Monthly Bill (Left) and Lock-in (Right) of Egos (Top) and Alters (Bottom) over a Period of 60 Days from 30 Days Before Listing Them to Call to 30 Days After Listing Them to Call



the alters who get offers from the firm and the one associated with the alters who do not. Please refer to Online Appendix I for more details on why this is the case. It is possible that, in our setting, (part of) the effect of listing alters to call on the churn rate of egos is associated with the alters who only get a satisfaction survey, which, according to the preceding arguments, may improve their opinion about the firm, resulting in a more positive signal that they transmit to egos. This can trigger mechanisms associated with both conformity and financial comparisons. Cialdini and Goldstein (2004, p. 606) define conformity as "the act of changing one's behavior to match the responses of others." If, in our setting, egos have a propensity to conform with their alters, the improved opinion that alters may have about the firm after going through the satisfaction survey may lead egos to stay more often with the firm under the *Call Ego and Alter* condition compared with what happens under the *Call Ego* condition (given that alters do not go through this survey under the latter condition). However, it may also be the fact that these alters did not get offers from the firm that provides an additional signal to egos under the *Call Ego and Alter* condition. Namely, egos have the same opportunities to align their monthly bills with those of their alters under the *Call Ego* condition and under the *Call Ego and Alter* condition. However, under the latter condition, the alters who picked up the phone from the firm and did not get an offer may have conveyed to egos that their monthly bills (that is, the monthly bills that egos can obtain if they accept the offers from the firm) seem hard to improve upon (because they were just recently on the phone with the firm and were unable to get a better deal). This type of mechanism, which we may call "on price" with low monthly bills for short, may also explain, in part, the observed lower churn rate across egos in our setting when alters are also listed to be called by the firm.

Finally, it is also possible that (part of) the effect of listing alters to call on the churn rate of egos is associated with the alters who get offers from the firm after they go through the satisfaction survey. Getting such an offer might again improve their opinion about the firm, resulting in a more positive signal that they transmit to egos. Furthermore, the alters that accept these offers—and, thus, renew their contracts with the

Table 6. Effect of Intention to Treat on Egos Controlling for Period Dummies and Churn Score

	Dependent variable			
	RR after 120 days		Churn by Jan. 2016	
	LPM		LPM	
	(1)	(2)	(3)	(4)
Call No One		0.017**		0.019***
		(0.007)		(0.006)
Call Alter	0.002	0.020***	−0.007	0.013**
	(0.009)	(0.007)	(0.008)	(0.006)
Call Ego	−0.017**		−0.019***	
	(0.007)		(0.006)	
Call Ego and Alter	−0.032***	−0.014**	−0.032***	−0.013**
	(0.009)	(0.007)	(0.008)	(0.006)
Churn score	0.127***	0.127***	0.050	0.050
	(0.035)	(0.035)	(0.032)	(0.032)
Constant	0.103***	0.085***	0.172***	0.153***
	(0.022)	(0.022)	(0.021)	(0.020)
Period dummies	Yes	Yes	Yes	Yes
Observations	45,023	45,023	45,023	45,023
R^2	0.002	0.002	0.003	0.003
Adjusted R^2	0.002	0.002	0.003	0.003
Residual standard error	0.391	0.391	0.355	0.355
F-statistic	8.123***	8.123***	12.570***	12.570***

Notes. Cluster robust and heteroskedastic consistent standard errors in parentheses. Observations clustered by social network treatment cluster. LPM, linear probability model; RR, reactive retention.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

firm—have just made (recent conscious) decisions to stay, which egos may copy, leading them to churn less under the *Call Ego and Alter* condition. In sum, both conformity and being on price with low monthly bills may lead egos to churn less with socially based proactive churn management.

5.3. The Effect of Churn Management on Firm Profit

Blattberg et al. (2008) discuss reasons why proactive churn management may be effective at keeping consumers but may, at the same time, fail to improve firm profits. In short, the firm tries to rescue likely churners, offering them good deals. However, and along this process, the firm may also end up delighting unlikely churners, who obtain lower monthly bills although they would have not churned even if they were not given such good deals. The former improves firm profit, and the latter does not. This trade-off is even trickier in the case of socially based proactive churn management because, in this case, the firm also calls alters, who are unlikely to churn, and thus, the likelihood of extending additional unnecessary deals may lower the profit of the firm even further. The appropriate way to determine the true effect of proactive churn management on firm profit is to measure its impact on customer lifetime value (CLV), which is what we do in our case. CLV is a function of the monthly bill, the survival with the firm, and the discount rate. In our analysis, we set the monthly bill of each household in our experiment to its observed level 120 days after treatment assignment.[1] We estimate survival as a function of treatment assignment using probabilistic continuous time models, which allow for churn rates to change over time (Fader and Hardie 2007, Schweidel et al. 2008). Online Appendix J provides the details of these computations and the results obtained. As expected, we find that the survival of egos increases when they are listed to be called by the firm and much more so when their alters are also listed to the called by the firm. The survival of alters does not change, on average, with treatment assignment. Finally, we set the discount rate to TELCO's weighted average cost of capital of 0.7%/month as reported to us by company managers. We use these data to compute CLV over a 10-year horizon (the average TELCO household stays 62 months with the firm).

Table 9 shows the results obtained from regressing CLV on treatment assignment, which, in our randomized setting, allows for immediately identifying the effect of socially based proactive churn management on the profit of the firm. Columns (1) and (2) show results for egos and columns (3) and (4) show results for alters. Column (1) shows that listing only alters to call does not change the CLV of egos in our setting. This column also shows that when only egos are listed to be called by the firm their CLV increases, on average, by 2.1% (51.1/(2861 − 663 × 0.7), where 0.7 is the average churn score across

Table 7. Effect of the Intention to Treat on Alters Controlling for Period Dummies and Churn Score

	Dependent variable	
	RR after 120 days (1)	Churn by Jan. 2016 (2)
Call Alter	−0.006	−0.004
	(0.005)	(0.005)
Call Ego	0.005	0.001
	(0.004)	(0.004)
Call Ego and Alter	−0.001	−0.003
	(0.006)	(0.005)
Churn score	0.113***	0.093***
	(0.005)	(0.005)
Flg. no churn score	0.038***	0.048***
	(0.003)	(0.003)
Constant	0.101***	0.085***
	(0.005)	(0.005)
Period dummies	Yes	Yes
Observations	74,748	74,748
R^2	0.007	0.008
Adjusted R^2	0.007	0.008
Residual standard error	0.314	0.272
F-statistic	44.269***	53.035***

Notes. Cluster robust and heteroskedastic consistent standard errors in parentheses. Observations clustered by social network treatment cluster. LPM, linear probability model; RR, reactive retention.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

egos in our sample). This column also shows that, when alters are listed to be called by the firm in addition to egos, the CLV of egos increases, on average, by 6.4% (154.3/(2861 − 663 × 0.7)). Column (2) shows that the difference between these statistics is statistically significant: 4.3% (given by 103.2/(2911 − 663 × 0.7)). This difference is the spillover effect associated with socially based proactive churn management, here measured in dollar terms for the firm. Columns (3) and (4) show that listing alters to be called by the firm, irrespective of whether egos are listed too, does not change their CLV, which is consistent with the fact that alters are unlikely to churn in our setting. Finally, and for robustness sake, columns (5) and (6) show the effects of our treatments over the clusters used in our experiment. The dependent variable in these regressions is the average CLV across egos and alters in each cluster (which adjusts for the fact that different clusters may have different sizes). The results in these columns confirm that, in our setting, listing likely churners to call is profitable for the firm and more so when their alters are also listed to be called.

6. Conclusions

This paper studies whether firms can actively use social network data to design an intervention that retains more consumers and increases profits compared with traditional proactive churn management. We do so in the context of triple play services, which is now becoming the standard mode of consumption in the telecommunications industry. In these markets, consumers become locked in for several months before they can churn without paying financial penalties, and there are no explicit network externalities in the way that they use services. Therefore, and at the outset, it was unclear whether peer effects would play a role in this type of market and, if so, whether they would be economically significant to lead firms to consider them when retaining consumers. The main contribution of our work is to suggest a new type of intervention to help firms retain likely churners. In particular, we suggest that firms should also contact their friends. This strategy, which we call socially based proactive churn management, is different from all previous approaches studied in the literature to perform proactive churn management, which involve contacting only likely churners. Yet socially based proactive churn management may work well if peer effects are

Table 8. Comparing Egos in the Call Ego and Call Ego and Alter Conditions in Terms of Picking up the Phone and Obtaining Offers from TELCO

	Get call (1)	Get offer (2)	Offer A (3)	Offer B (4)	Offer C (5)
Call Ego and Alter	0.002	0.004	−0.002	−0.001	0.002
	(0.008)	(0.008)	(0.002)	(0.005)	(0.007)
Churn score	−0.119**	−0.132***	−0.009	−0.109***	−0.020
	(0.047)	(0.044)	(0.011)	(0.030)	(0.039)
Constant	0.565***	0.411***	0.040***	0.170***	0.207***
	(0.030)	(0.028)	(0.008)	(0.019)	(0.025)
Period dummies	Yes	Yes	Yes	Yes	Yes
Observations	37,132	37,132	37,132	37,132	37,132
R^2	0.083	0.060	0.007	0.062	0.047
Adjusted R^2	0.083	0.060	0.006	0.062	0.047
Residual standard error	0.479	0.460	0.097	0.275	0.426
F-statistic	372.823***	264.260***	27.357***	271.390***	204.269***

Notes. Cluster robust and heteroskedastic consistent standard errors in parentheses. Observations clustered by social network treatment cluster.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 9. Effect of Treatment Assignment on the Expected Lifetime Value of Egos, Alters, and Clusters in Our Experiment

	Dependent variable					
	CLV(CF, WACC = 0.7%, T = 120)			CLV(CF Cluster, WACC = 0.7%, T = 120)/Size		
	Egos (1)	Egos (2)	Alters (3)	Alters (4)	Cluster (5)	Cluster (6)
Call No One		−51.089**		−27.926		−35.646*
		(23.115)		(23.848)		(18.957)
Call Alter	46.915	−4.174	36.463	8.536	39.456	3.810
	(31.224)	(23.729)	(32.328)	(24.670)	(25.479)	(19.212)
Call Ego	51.089**		27.926		35.646*	
	(23.115)		(23.848)		(18.957)	
Call Ego and Alter	154.289***	103.200***	11.668	−16.258	85.095***	49.449**
	(31.390)	(23.913)	(32.745)	(25.195)	(25.812)	(19.632)
Churn score	−663.122***	−663.122***	−1,874.305***	−1,874.305***		
	(132.104)	(132.104)	(28.438)	(28.438)		
Flg. no churn score			−1,069.167***	−1,069.167***		
			(23.209)	(23.209)		
Cluster churn score					−1,134.396***	−1,134.396***
					(36.951)	(36.951)
Constant	2,860.568***	2,911.657***	3,757.427***	3,785.354***	3,381.876***	3,417.522***
	(82.575)	(80.583)	(30.052)	(23.259)	(26.204)	(21.030)
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,023	45,023	74,748	74,748	43,582	43,582
R^2	0.033	0.033	0.066	0.066	0.045	0.045
Adjusted R^2	0.033	0.033	0.066	0.066	0.044	0.044
Residual standard error	1,382.494	1,382.494	1,825.165	1,825.165	1,105.293	1,105.293
F-statistic	138.898***	138.898***	440.860***	440.860***	185.412***	185.412***

Notes. Columns (1)–(4): Cluster robust and heteroskedastic consistent standard errors in parentheses. Columns (1)–(4): Observations clustered by social network treatment cluster. Columns (5) and (6): Heteroskedastic consistent standard errors in parentheses. Household survival projected using log-logistic model. CF, monthly bill 120 days after listing in the experiment; CLV, customer lifetime value; WACC, weighted average cost of capital.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

sufficiently strong to create enough goodwill around likely churners to help retain them. However, strong peer effects may not be sufficient for a firm to take advantage of this strategy because, in the process of creating such goodwill, the company might extend good deals to an unreasonable number of friends of likely churners (who could be unlikely to churn). This may hurt the firm's profit. If, however, a strong effect of peer influence can be achieved without losing too much revenue on the friends of the likely churners, then it is possible that reaching out to the latter becomes profitable for the firm.

We collaborated with a major telecommunications provider to design, implement, and analyze outcomes of a randomized control trial at the household level, allowing us to study the effects associated with socially based proactive churn management. We started by using data from call detailed records to draw a social graph across households and data from pay-TV subscriptions to develop a model to predict likely churners. Subsequently, and on a monthly basis during eight consecutive months, we selected a random set of likely churners and their friends and we allocated them randomly across four different experimental conditions. In the *Call No One* condition, all households were listed not to be called by the firm. In the *Call Ego* condition, likely churners were listed to be called by the firm and their friends were listed not to be called by the firm. In the *Call Alter* condition, the friends of likely churners were listed to be called by the firm and likely churners were listed not to be called by the firm. Finally, all households in the *Call Ego and Alter* condition were listed to be called by the firm. All calls were routed through the firm's call center, and the call center agent associated to each call was also randomized. Randomly assigning households to these conditions allows us to immediately identify both the effect of proactive churn management—by comparing churn rates across the *Call Ego* and the *Call No One* conditions—and the effect of socially based proactive churn management by comparing churn rates across the *Call Ego and Alter* and the *Call Ego* conditions. On average, we find that likely churners listed to be called by the firm whose friends were listed not to be called reduce their likelihood of churn by 1.9 percentage points ($p < 0.01$) from a baseline of 17.2%. The likelihood of likely churners listed to be called by the firm whose friends were also listed to be called reduce the likelihood of churn by an additional 1.3 percentage points ($p < 0.05$).

Our findings show that, in our setting, a signal flows from alters to egos that lowers the likelihood at which the latter enter reactive retention and churn. This signal may trigger several mechanisms that may lead egos to churn less with socially based proactive churn management. The satisfaction survey that alters go through when they pick up the phone from the call center may, just per se, improve their opinion about the firm, which may lead them to transmit a more positive signal to egos—likewise for alters who obtain and accept offers from the firm. If, in our setting, egos have a propensity to conform with their alters, that is, if they exhibit a tendency to align their opinion with those of their alters and copy their behavior, then these improved signals may lower the churn rate of egos when alters are also listed to be called by the firm compared with when they are not. However, a lower churn rate across these egos may also arise because of the signal transmitted by the alters who pick up the phone from the firm and do not obtain offers. These alters may convey to their egos that if they accept the offers that they get from the firm then they obtain monthly bills that seem hard to improve upon. This idea of on price with low monthly bills may also decrease the likelihood of churn across egos whose alters have been listed to be called by the firm.

In addition, we use the framework proposed in Blattberg et al. (2008) to measure the effect of our interventions on firm profit using customer lifetime value. The additional CLV associated with traditional proactive churn management is $51.10 per likely churner, which represents an increase of 2.1% compared with reactive retention. These statistics are $154.30 and 6.4%, respectively, for the case of socially based proactive churn management. Furthermore, we find no changes in the CLV of the friends of likely churners relative to reactive retention both with traditional and socially based proactive churn management. Therefore, we show that, in our context, socially based proactive churn management reduces churn among likely churners and increases firm profits. Although a single empirical case is not enough to generalize results, we believe that our findings may extend to other contexts similar to ours, namely to subscription-based settings without explicit network externalities, in which mechanisms akin to financial comparisons and conformity play a role. Our paper suggests a new direction to enrich the firms' current portfolios of churn management strategies. Therefore, our results have significant implications for churn managers at firms that know, or that can proxy, the social network across their consumers and shows one way in which they can apportion value to these data.

Finally, we note that our work does not come without limitations. First, we do not observe the messages exchanged by egos and their friends. We have evidence that, in our setting, a signal flows from the latter to the former that reduces the churn rates of likely churners, but we are unsure about what this signal is, when is it transmitted, or what communication medium is used to transmit it. Second, part of the success of the churn management interventions that we test with our experiment is associated with the performance of the call center agents. This is not a special feature of our setting but rather an attribute common to all churn management exercises; in other words, one cannot expect to obtain good results from proactive churn management with unskilled call center agents. Third, our experiment did not attempt to identify which offers provided by the firm maximized the additional effect associated with socially based proactive churn management. A field experiment that randomizes the offers extended by the firm at the household level would be an appropriate next step to further the analysis that we performed in this paper. Fourth, we acknowledge that there are many ways in which one can identify customers at risk; in particular, the most likely churners might not be the most valuable customers to the firm or the ones that are easier to retain. Therefore, the value generated by socially based proactive churn management may even be higher that what we report in our paper if one combines targeting groups of consumers with more appropriate models to identify profitable targets.

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Endnotes
[1] About 95% of true positives listed by our predictive model request to disconnect their service (that is, enter the reactive retention) in the first 120 days after being identified by our model.

[2] Of true positives listed by our predictive model, 95% request to disconnect their service (that is, enter the reactive retention) in the first 120 days after being identified by our model.

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