Irit Nitzan & Barak Libai

Social Effects on Customer Retention

This study explores the role of customers' social network in their defection from a service provider. The authors use data on communication among one million customers of a cellular company to create a large-scale social system composed of customers' individual social networks. The study's results indicate that exposure to a defecting neighbor is associated with an increase of 80% in the defection hazard, after controlling for a host of social, personal, and purchase-related variables. This effect is comparable in both magnitude and nature to social effects observed in the highly researched case of product adoption: The extent of social influence on retention decays exponentially over time, and the likelihood of defection is affected by tie strength and homophily with defecting neighbors and by these neighbors' average number of connections. Highly connected customers are more affected, and loyal customers are less affected by defections that occur in their social networks. These results carry important implications for the theoretical understanding of the drivers of customer retention and should be considered by firms that aim to predict and affect customer retention.

Keywords: customer retention, social networks

It has been acknowledged for some time that the adoption of new behaviors or innovations may be substantially affected by social interactions with others (Rogers 2003; Ryan and Gross 1943). Across several disciplines, there is a growing realization that quitting behavior may be socially affected as well. For example, researchers have shown that people are socially affected by others, sometimes to a large degree, in cases of quitting smoking (Christakis and Fowler 2008), defecting from military service (De Paula 2009), or leaving employment in a firm (Castilla 2005).

Marketers should be interested in this phenomenon because of its possible implications for understanding and predicting customer retention. Over the past two decades, practitioners and academics have paid considerable attention to customer retention and to its antecedents and consequences, primarily because of the impact of retention on customer lifetime value and consequently on the firm's bottom line (Bolton 1998; Rust and Chung 2006; Verhoef 2003; Villanueva and Hanssens 2007). However, almost all marketing-related analysis on social effects among customers has focused on customer acquisition, and particularly on the adoption of new products, rather than on customer retention.

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Here, we present a first-of-its-kind analysis of the effects of social environment on customer retention. In this analysis, we use a database of more than one million customers of a cellular company in a Mediterranean country. Researchers are increasingly using telecommunications databases to explore social network behavior (Hill, Provost, and Volinsky 2006; Onnela et al. 2007), and recent studies suggest that cellular networks serve as a good proxy for real social networks (Eagle, Pentland, and Lazer 2009). Using data on the communication among customers, we were able to create a large-scale social system composed of customers' social networks. Because our social system includes all the personal customers of the company rather than a sample, we avoid the nontrivial problems associated with network-related analysis based on sampling from large-scale networks (Monge and Contractor 2003).

We combine social network information with data on customer retention to assess the extent to which a customer who leaves the company might be affected by the past defections of other members in his or her direct personal social network (whom we label "neighbors").

We estimate two proportional hazard models: a traditional model, which takes into account customer satisfaction, usage patterns and demographics (Bolton 1998; Bolton and Lemon 1999); and a social model, which includes, in addition to the variables of the traditional model, the social aspects that may drive customers' defections (e.g., exposure to a defecting neighbor, the size and characteristics of each customer's social network). We can summarize our results as follows:

- *The extent of the social effect*: We find that the social aspects we evaluate have a sizeable impact on defection and that the inclusion of social variables increases the explaining power and predictive power of the customer defection model. For example, when controlling for a host of personal, satisfaction-related, purchase-related, and social variables, we observe

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that a neighbor's defection is associated with an increase in the hazard of a focal customer's defection of approximately 80%. This effect is comparable to and even higher than most reported effects in the domain of adoption, and it holds when the level of advertising by various competitors is taken into account.

- *The nature of the social effect*: We determine that the pattern of social effects on customer defection is consistent with reported patterns related to adoption, which suggests that defection and adoption are driven by similar mechanisms. We observe that the hazard of defection increases with tie strength with defecting neighbors and with homophily with defecting neighbors, and it decays exponentially with time. Furthermore, we observe that customers with greater numbers of social connections are more likely to defect; a similar phenomenon is observed in the case of adoption, in which highly connected "network hubs" adopt earlier (Goldenberg et al. 2009). Regarding customers who affect others, we find that highly connected customers might affect others more weakly than customers with fewer connections. A customer's hazard of defection decreases as the average degree of his or her defecting neighbors increases. Moreover, we find that customer loyalty may help "immunize" customers against the effect of the defection of others: Heavy users and customers with higher tenure are less affected by neighbors' defections than light users and newer customers, respectively.

Our findings contribute to current literature in several ways. First, they underscore the need to further study the social aspects of customer retention. They suggest that the tools and mechanisms used to study social effects on customer acquisition can be used to study the social effects on their retention. From a practical aspect, our work sheds light on the need to incorporate social effects into the widely used churn-prediction models (Neslin et al. 2006), which have historically ignored intercustomer dynamics. Second, these findings contribute to knowledge on the drivers and consequences of customer loyalty, and from a social effects perspective, they provide further insight into the contribution of customer loyalty to the bottom line. Third, these results highlight the need to formally examine various social effects and provide relatively rare empirical evidence of how social effects among customers decay over time. Finally, we demonstrate how large-scale telecommunications databases can be used to supply researchers with a rich platform that enables them to study actual consumption behavior over time in the presence of social effects.

Background

Traditional Retention Drivers

The importance of customer retention stems mainly from its close connection to a firm's bottom line (Reinartz and Kumar 2003; Rust and Chung 2006); retention typically serves as a mediator in the satisfaction–profitability link (Rust, Lemon, and Zeithaml 2004; Villanueva and Hanssens 2007). Although there is a debate as to the precise mechanisms of the relationship between retention and profit, in general, researchers agree on the importance of retention as a key driver of a firm's profitability, and it is repeatedly treated as a critical component in customer profitability models (Bolton, Lemon, and Verhoef 2004; Gupta et al. 2006). This perspective is reflected in the considerable attention that firms devote to building predictive models of customer churn (Neslin et al. 2006).

Numerous studies have attempted to examine retention drivers (Gustafsson, Johnson, and Roos 2005; Lemon, Barnett-White, and Winer 2002; Rust and Chung 2006; Verhoef 2003; Villanueva and Hanssens 2007). Several drivers of retention emerge as especially prominent; we elaborate on these in the following paragraphs.

Customer satisfaction serves as a key element in customers' defection decisions (Bolton 1998; Oliver 2009). Researchers have either explored satisfaction at a single point in time (Gustafsson, Johnson, and Roos 2005; Mittal and Kamakura 2001) or considered it a measure that evolves over time (Bolton and Lemon 1999; Bolton, Lemon, and Bramlett 2006; Cooil et al. 2007), and they have evaluated satisfaction either on the basis of customers' self-reports or by making inferences from customer behavior.

Usage pattern, also considered a consequence of customers' fairness perception (Bolton and Lemon 1999), is typically analyzed as a trend in customers' usage, suggesting that a decrease in customers' usage levels may serve as a key signal of their eventual defection. Related findings indicate that low usage levels, which may also be represented by share of wallet (Verhoef 2003), are positively related to customers' likelihood of remaining with the firm (Reinartz and Kumar 2003). *Customer tenure* with the company has been found to negatively affect customers' intentions to defect (Bolton 1998; Cooil et al. 2007) and to further enhance the positive effect of satisfaction on customer retention (Verhoef 2003). *Personal characteristics* (Bolton 1998), such as customers' gender (Cooil et al. 2007; Mittal and Kamakura 2001) and age (Baumann, Burton, and Alliott 2005), have been found to significantly affect customers' defection decisions in various industries including financial services, communication services and the auto industry.

In light of these efforts, the absence of research on social influence as a defection driver is evident, especially given strong findings from the diffusion-of-innovation literature, in which social influence has been established to have a notable effect on a consumer's adoption decision (Keller and Berry 2003; Peres, Muller, and Mahajan 2010; Rogers 2003; Van den Bulte and Wuyts 2007).

Retention and Social Influences

Social influence stems from the transmission of various pieces of information among people who are connected to one another. This transmission can occur through a variety of interactions a person has with others in his or her social circle. For example, a person may receive information about a product by behavioral learning (e.g., seeing another person with the product, talking to another person about the product (word of mouth), receiving third-party information about another person who uses the product). Social influence can occur through the transmission of information that reduces uncertainty and search effort, through normative and social pressure, or as a result of network externalities (Peres, Muller, and Mahajan 2010; Van den Bulte and Lilien 2001).

It is not a priori clear whether the extent of social influence on customer defection is similar to that on adoption. In contrast to the case of adoption, potential defectors have gained their own knowledge about the brand and may not need to rely so much on others. For example, consider the cellular services industry, which we study here. By 2008, when this empirical study took place, the industry was mature and the value of risk reduction that social influence had supplied in previous years had probably decreased substantially. It could be argued that currently, because customers are relatively knowledgeable of the industry, their defection decisions might be affected by the level of service they experience, the switching costs stipulated in their contracts, and promotions by other companies.

In contrast, defections are often associated with negative word of mouth that drives further defections (Wangenheim 2005). It is widely accepted that negative word of mouth has a relatively stronger effect than positive word of mouth (Goldenberg et al. 2007; Nam, Manchanda, and Chintagunta 2010). Furthermore, consumers may notice and discuss other people's defections, and this might serve to legitimize planned defections that have not taken place yet. Indeed, results regarding social influence on behavior termination in non-brand-related actions such as quitting smoking (Christakis and Fowler 2009) also support possibly sizeable social effects on defections. Thus, our first aim is to assess the extent to which customer defections have social effects on the defection decisions of others.

We focus on a person's close social network; this network often plays a major role in a consumer's purchase decisions (Godes and Mayzlin 2004; Van den Bulte and Wuyts 2007). One of the challenges associated with such an investigation is that people in the same social network may be affected by unobserved correlations that will drive them to defect at approximately the same time regardless of the social connection (Manski 2000). Therefore, we must take into account data on social network members, their attributes, and their usage patterns when aiming to identify social effects. Here we control for a host of variables that include satisfaction, usage pattern, tenure with the provider, and demographics.

Our second aim is to portray the nature of the social effects on retention. Because the mechanisms of social effects have been studied extensively in the context of adoption of innovations, it is of interest to explore whether the same mechanisms operate in the case of retention or whether we need to update our knowledge on social effects in this respect. Specifically, we investigate tie strength, homophily, degree of connectivity, and the effect of time. We elaborate on each factor in the following subsections.

Tie strength. Prior adoption-related studies have indicated that consumers may be more affected by people with whom they have closer relationships (Brown and Reingen 1987). Thus, a closer relationship, as perceived by the focal customer, may also have a stronger effect on the customer's defection decision. The strength of tie may signify the intensity and tightness of a social relationship (Van den Bulte and Wuyts 2007), and researchers have found it to influence referral behavior among social contacts (Brown and Reingen 1987; Ryu and Feick 2007). Relationships may range from strong, primary relationships, such as a spouse or close friend, to weak, secondary relationships, such as seldom-contacted acquaintances (Reingen and Kernan 1986). In the context of customers' exposure to defecting neighbors, we determine the extent to which the strength of a focal customer's social ties with defecting neighbors contributes to that customer's defection probability.

Homophily. In the context of adoption, researchers have suggested that referral behavior often takes place among actors (customers) who are similar to one another in beliefs, education, and occupation (Brown and Reingen 1987; Rogers 2003). This tendency may stem from the notion that customers are more likely to trust the endorsements of people whose preferences they share and, conversely, that endorsers are likely to feel more comfortable sharing experiences with people who are similar to them (Feick and Higie 1992). The measure of homophily reflects the level of similarity between two people who take part in a social tie, that is, how alike they are with respect to their personal attributes. We investigate the extent to which such similarity between a focal customer and a defecting neighbor affects the focal customer's defection decision.

Degree of connectivity. Probably the most commonly used measure of centrality in networks, degree centrality represents the connectivity of a person in the network (Monge and Contractor 2003). The degree of a social entity is defined as the number of other entities directly related to that entity, which in our case is reflected in the number of direct neighbors of the focal customer. Highly connected customers are typically considered to have the opportunity to affect others' behavior (Barabasi 2003; Van den Bulte and Wuyts 2007). Furthermore, people with numerous connections might also be more strongly affected by the behavior of others: For example, Goldenberg et al. (2009) suggest that network hubs adopt earlier because of their connectivity. If this is the case in defection decisions as well, we may expect that customers with more connections will defect early (i.e., have a greater hazard of defection). In contrast, if we consider attention a limited resource, a customer with a greater number of connections may devote, on average, less attention to each connection (Katona, Zubcsek, and Sarvary 2011). As a result, a customer with more connections might actually have a weaker effect on the defection decisions of others. We explore two aspects of connectivity to determine its effect on a customer's hazard to defect. First, we investigate whether a focal customer with higher connectivity is more likely to defect (similarly to the case of adoption). Second, we examine the effect of the average degree of the defecting neighbors the focal customer was exposed to in a given month.

The effect of time. An interesting question is related to the possible temporal aspect of social effects on retention. In the adoption literature, there are some indications that the effect of word of mouth decays exponentially over time (Strang and Tuma 1993; Trusov, Bucklin, and Pauwels 2009). Here, we consider two events of interest—a neighbor's previous defection and the customer's current one—to determine whether, as in the case of adoption, the social effect of a defection event decays exponentially over time.

Data

We carry out our investigation in the context of the cellular industry. We focus on this industry because of the availability of customer network data and also because cellular markets have been widely researched in terms of both adoption and churn. Regarding adoption, it is widely accepted that social effects play a role in the diffusion of products in this category (Libai, Muller, and Peres 2009; Manchanda, Xie, and Youn 2008). While churn in this industry is a key managerial variable, historically applied churn models have not incorporated social network aspects.

Our data come from the cellular phone industry in a Mediterranean country in 2008. In that year, there were three main competitors in the market. The market was mature and saturated, so attrition would most likely be reflected in a defection to a competitor rather than abandonment of cellular service. The coverage in this country is considered exceptional, and there are practically no uncovered areas; therefore, we can assume that across geographical areas, the customers of this provider experienced the same level of service. To protect customers' privacy, each phone number was encrypted in a way that still enabled us to track that number through the entire research data set. Payments in this country are for outgoing calls only, and the monthly bill is based on actual minutes of use (MOU) and not on prepurchased minute blocks.

The cellular communication industry has historically been characterized by a pricing-driven network effect (Farrel and Klemperer 2007). In practice, providers have generated this effect by offering subscribers cheaper rates for calls within a specific provider's network. According to interviews conducted with managers of the cellular firm that supplied the data, although out-of-network differential pricing was more common in the past, by the beginning of 2008, more than 80% of the customers belonged to plans in which there was no differential pricing among networks. In the following section, we delineate the data sets used in this study.

Communication Data Set

The communication data set includes information on the communication behavior of all personal customers of a cellular provider in this country (approximately 1.1 million customers); this behavior was tracked over the course of 2008. The research focuses on personal, postpaid customers (85% of personal users in this market). Owing to the challenges associated with identifying a complete relevant network in large-scale networks, most studies in the literature have examined social processes using samples of such networks. However, researchers have recommended avoiding social network sampling when possible (Monge and Contractor 2003), as it may introduce errors and biases (Barrot et al. 2008). Fortunately, we had access to the entire communication database of the cellular provider, which enabled us to construct a complete social network and identify all the network neighbors (i.e., direct contacts) of every customer. We did not have access to detailed communication beyond the provider's network; however, the total MOU and the number of text messages are captured.

Consistent with Onnela et al. (2007), we used three months of data on communication between customers to reconstruct each customer's social network within the provider's network. This is the base map, and it is composed of communication data from January to March 2008. The ties within this network are described in an undirected way (i.e., "A called B" is grouped together with "B called A") because we are not interested in the initiator of the calls but rather in the existence of the link and the volume of communication conducted by the two parties.

The customers in the database conducted 49.6 million calls and exchanged 12.7 million text messages within the provider's network during a typical month. These communication interactions are represented in a network that has an average degree of 12.1 and contains approximately 14 million links (representing communication conducted between the customers in the network). The network's clustering coefficient, which represents the clustering level of the social network, is .17, which is generally consistent with observations for reported social networks.

Satisfaction Data Set

Because of the large number of customers in this data set, it is impractical to obtain a direct, stated measurement of each customer's satisfaction. Therefore, we used two measures to represent customer satisfaction. The first, following Bolton and Lemon (1999), is customer usage trends; we rely on the notion that a decrease in a customer's usage level over time may indicate dissatisfaction. The second is the number of service records documented in each customer's file, as captured from the firm's database. Whenever a customer contacts the service provider (through either the company's call center or its physical service centers), a customer service representative documents the request. Complicated issues require longer documentation, which may consist of several service records. Thus, the quantity of a customer's complaints and recurring questions are reflected in the number of such records, which can be used as a proxy for the customer's satisfaction level. We calculated both satisfaction measures on a monthly basis.

Demographics

We also had access to four sociodemographic characteristics of the provider's customers: gender, age, segment, and socioeconomic status (taken from a zip code database), as well as information regarding the date on which the customers joined the provider's service (and thus their tenure).

Defections Data Set

We capture every defection that occurred among the customers in the database throughout 2008, according to the exact date of defection. To determine a defection, we used the following criteria: Either the customer announced the defection, or it was determined according to the provider's definition of a defecting customer, which is consistent with industry standards (i.e., the customer has not used the phone for six months for either incoming or outgoing calls or for any other purpose). Some network externality effects in the context of the cellular industry may be attributed to family plans in which a family gets a lower rate for within-family calls. Thus, in our case, when members of a family move to another supplier at the same time, we count it as one defection.

With regard to the extent to which customers were exposed to their neighbors' defections, we find that most customers (66.0%) in our data set were not exposed to any defecting neighbors in their immediate networks in 2008, approximately 22% of the customers were exposed to one neighbor who defected, 7.8% were exposed to two neighbors who defected, and the rest (approximately 4%) were exposed to three or more defecting neighbors in 2008 (see Figure W1 in Part A of the Web Appendix at http://www.marketingpower.com/jmnov11).

Methodology

Survival analysis techniques are widely used in marketing to study various event occurrences related to the duration of consumption behavior (Helsen and Schmittlein 1993; Landsman and Givon 2010). We use a proportional hazard model (Kleinbaum and Klein 2005), a technique researchers frequently use to model the duration of the customer–provider relationship as well as the probability of a customer's ending it (Bowman 2004). There are two important advantages of this method over standard regression methods such as ordinary least-squares or logistic regression. First, the proportional hazard model takes into account right censoring. (In our case, only 4.1% of the customers churned in the year analyzed, so right-censoring is an issue to consider.) This is of particular importance because right-censoring can deceive researchers into finding evidence for contagion when there is none (Van den Bulte and Iyengar 2011). Second, it has the capacity to analyze both time-constant independent variables (e.g., demography) and time-varying independent variables. Variables such as exposure to defectors can change over time, so this is an essential advantage in our case.

In our model, the dependent variable is the hazard of defection. A customer who has defected is considered lost for good; this assumption is reasonable given the post-paid contractual nature of the industry studied, as well as the limited time frame we use. As in De Paula (2009), we evaluate monthly time-discrete data, which we use to approximate a continuous-time process. We tested the hazard proportionality assumption using the Kaplan-Meier curves for each covariate and found that it fits well. The issue of left-censoring should also be considered here because customers joined the service at different times. We take this issue into account by incorporating each customer's tenure with the service provider (the number of months that passed from the customer's enrollment until January 2008) into the model (Allison 1995).

In the semiparametric partial likelihood estimation we use, the hazard rate $h_i(t \mid x_{it})$ represents the hazard of customer i, whose individual characteristics are captured by vector x_{it}, of defecting at time t, and it is assumed to take the following form: $h_i(t \mid x_{it}) = h_0(t)\exp(\beta' x_{it})$, where $h_0(t)$ is the baseline hazard function, which captures the longitudinal effect, and β' represents the effect of the variables composing x_{it} on the hazard rate. This estimation enables us to assess the parameters of interest without specifying the baseline hazard $h_0(t)$. In large samples (as in this study), the estimates produced by this approach are consistent and asymptotically normal (Allison 1995).

Variables

Social Variables

Exposure. The exposure variable represents the presence of previous defectors in the social system of a defector. As we noted previously, we refer to immediate (first-degree) social system members as neighbors. We consider exposure to defecting neighbors a time-varying variable and define the exposure of customer i in month t as the following sum:

$$\text{Exposure}_{i,t} = \sum_{j \in SN_i} \delta_{j,t},$$

where j denotes a customer who belongs to customer i's immediate social network (SN_i) (i.e., j is a neighbor of i), and $\delta_{j,t}$ is a binary variable serving as a flag, which takes a value of 1 if customer j defected in month t and 0 if otherwise.

In addition to the basic exposure, we examine the lagged exposure, which reflects focal customer i's exposure to defecting neighbors at several points in time (e.g., exposure to defecting neighbors in the current period, exposure to defecting neighbors in the previous period, and exposure to defecting customers two periods ago).

Tie strength. Following previous studies (e.g., Onnela et al. 2007), we used the volume of communication between each pair of customers as an indicator of the strength of the tie between those customers. We define customers' communication volume for each pair of customers, and it refers to the sum of minutes these customers spent talking (conversations initiated by either of them) and the number of text messages they exchanged. We consider a text message equivalent to one minute of talk. We calculate the tie strength (TS) between customer i and customer j, from i's perspective, as follows:

$$TS_{i,j} = \frac{\text{Comm\_Vol}_{i,j}}{\text{Total\_Comm}_i},$$

where $\text{Comm\_Vol}_{i,j}$ represents the communication volume between the focal customer (i) and his or her neighbor j ($j \in SN_i$; i.e., j belongs to the social network of i) and Total_Comm_i is the total volume of communication that i conducted within the network.

We use the individual-level tie strength to calculate the average tie strength with defecting neighbors (avgTS). For each focal customer i in month t, we calculated avgTS as follows:

$$\text{avgTS}_{i,t} = \frac{\sum_{j \in SN_i} TS_{i,j} \times \delta_{j,t}}{\sum_{j \in SN_i} \delta_{j,t}},$$

where, as mentioned previously, $\delta_{j,t}$ is a binary variable (0 or 1) that reflects a previous defection of a member of i's social network in month t. If $\sum_{j \in SN_i} \delta_{j,t} = 0$, then $\text{avgTS}_{i,t} = 0$.

Homophily. Following Brown and Reingen (1987), we measured customers' homophily as the percentage of similar characteristics a pair of connected customers share. There are four sociodemographic characteristics in our data (gender, age, segment, and socioeconomic status). To evaluate the homophily between any two customers, we assigned a score of .25 points for each variable that was similar between the two customers, and the final homophily score was the sum of these points. Thus, homophily between two customers could range from 0 (no match) to 1 (full match). We used binary variables (match/no match) to indicate similarity of gender, segment, and socioeconomic status and determined ages to be similar if the difference between them was less than five years.

Similar to the case of tie strength, we calculated each customer's average homophily with defecting neighbors (avgH). For each focal customer i in month t, we calculated avgH as follows:

$$\text{avgH}_{i,t} = \frac{\sum_{j \in SN_i} H_{i,j} \times \delta_{j,t}}{\sum_{j \in SN_i} \delta_{j,t}},$$

where, as mentioned previously, customer j is a neighbor of customer i ($j \in SN_i$) and $\delta_{j,t}$ is a binary variable (0 or 1) that reflects whether customer j defected in month t. If $\sum_{j \in SN_i} \delta_{j,t} = 0$, then $\text{avgH}_{i,t} = 0$. The term $H_{i,j}$ represents the level of homophily between the focal customer i and neighbor j.

Degree. Each customer's total degree within the network represents the number of unique persons with whom this customer communicated during the first three months of data (January–March 2008). We refer to these customers as the neighbors of the focal customer.

We also consider the degree of the defecting neighbors to whom the focal customer was exposed. We calculate the average degree of defecting neighbors ($\text{avgDEG}_{i,t}$) for each focal customer i in month t as follows:

$$\text{avgDEG}_{i,t} = \frac{\sum_{j \in SN_i} \text{DEG}_j \times \delta_{j,t}}{\sum_{j \in SN_i} \delta_{j,t}},$$

where the term DEG_j represents the degree of neighbor j.

Satisfaction-Related Variables

We use two satisfaction-related variables: change in the level of usage and the number of service records. Previous research has suggested that change in use may indicate dissatisfaction (e.g., due to equity perception; Bolton and Lemon 1999). To avoid scale differences among customers as well as bias caused by fluctuations in customers' usage levels over time, we refer to the proportion of the current month's usage level ($\text{Use}_{i,t}$) to the average usage in the three months preceding that month:

$$\Delta\text{Use}_{i,t} = \frac{\text{Use}_{i,t}}{\text{average}(\text{Use}_{i,t-1}, \text{Use}_{i,t-2}, \text{Use}_{i,t-3})}.$$

We captured the second satisfaction-related variable, total number of service records in each customer's file, documented by service representatives of the company, on a monthly basis.

Economic Incentive

Although 80% of the customers at the time of the study were not charged differential prices for out-of-network calls, such pricing did apply to some customers. In addition, one could wonder if some customers might have perceived such a difference because they had been exposed to such pricing plans in the past. Thus, it is useful to determine whether part of the social effect can be attributed to network effects. However, separating word-of-mouth effects from network externalities continues to be a challenging task for researchers (Goldenberg, Libai, and Muller 2010; Van den Bulte and Stremersch 2004).

To help us understand the influence of network externalities, we include in the model a control variable that reflects the possible economic considerations of a given customer. The idea is to separate a customer's communication pattern into within-network versus out-of-network communication. The ratio of the within-network communication, measured in monthly MOU, denoted Within_Network_MOU, to the total MOU (within network + out of network; denoted Total_MOU) is a variable we label economic incentive (EI):

$$\text{EI}_i = \frac{\text{Within\_Network\_MOU}_i}{\text{Total\_MOU}_i}.$$

We expect that an increase in the EI value for a given customer will be associated with a decrease in the hazard of defection because a neighbor's defection will result in a greater economic loss to that customer (network externalities).

Other Variables

In addition to the variables mentioned previously, we included in the hazard model the control variables that were available to us. These include usage, tenure (time with the supplier), age, gender, and membership in several sociodemographic segments as identified by the supplier. Tables W1, W2, and W3 in Part A of the Web Appendix (http://www.marketingpower.com/jmnov11) provide more information about the variables used in this study.

The Defection Hazard Model

We estimate three models to examine the social effects of defections. Model 1, the *traditional model*, tests the effects of previously explored variables found to affect consumers' tendency to defect.[1] These variables include satisfaction, represented by the level of service consumption (service records) and the usage trend, economic incentive, and some demographic characteristics:

$$(1) \qquad h_i(t \mid x_{it}) = f(\text{ServiceRec}_{i,t}, \Delta\text{Use}_{i,t}, \text{avgEI}_i, \text{avgUsage}_i, \text{Tenure}_i, \text{Demography}_i).$$

Model 2, the *social model*, adds five social variables to the variables estimated in the traditional model to account for the social aspects in the defection process. We test the effects of the following on a given customer's hazard of defection: the customer's exposure to defecting neighbors, tie strength between the customer and defecting neighbors, homophily between the customer and defecting neighbors, the average degree of the customer's defecting neighbors, and the customer's social connectivity (degree) in the network:

$$(2) \qquad h_i(t \mid x_{it}) = f(\text{Exposure}_{i,t}, \text{avgTS}_{i,t}, \text{avgH}_{i,t}, \text{avgDEG}_{i,t}, \text{Degree}_i, \text{ServiceRec}_{i,t}, \Delta\text{Use}_{i,t}, \text{avgEI}_i, \text{avgUsage}_i, \text{Tenure}_i, \text{Demography}_i).$$

Model 3 is aimed at demonstrating the effect of exposure to a defecting neighbor over time; therefore, we incorporated several lagged-exposure variables into this

[1]We thank an anonymous reviewer for suggesting this approach.

model. Exposure_{t-1} represents the exposure to defecting neighbors whose defections occurred in the period (month) before month t, Exposure_{t-2} is the exposure to defecting neighbors whose defections occurred two periods before month t, and so on. Note that to highlight this effect, we focus on the incremental effect of the focal customer's exposure to defecting neighbors in various time gaps while controlling for the basic control variables introduced previously:

$$(3) \qquad h_i(t \mid x_{it}) = f(\text{Exposure}_{i,t}, \text{Exposure}_{i,t-1}, \text{Exposure}_{i,t-2}, \text{Exposure}_{i,t-3}, \text{Exposure}_{i,t-4}, \text{avgEI}_i, \text{avgUsage}_i, \text{Tenure}_i, \text{Demography}_i).$$

Identification

The attempt to infer social influence from observational data raises questions of identification (Hartmann et al. 2008; Manski 2000). Such social influences are sometimes referred to as peer effects. It can be argued that social neighbors (peers) might defect at roughly the same time, not as a result of informational or economic social influence, but rather due to other reasons, referred to in the literature as unobserved correlations. Next, we specify how we attempted to mitigate the possible biases.

Unobserved similarities in customers' preferences and tastes. Product adoption (or defection) similarities may reflect customers' intrinsic tendency to behave similarly (Barrot et al. 2008; Manski 2000). To account for such possibilities, past models have incorporated variables that might indicate similarity, such as demographics (Barrot et al. 2008; Nair, Manchanda, and Bhatia 2010). We included several demographic variables (e.g., gender, sociodemographic group) and usage characteristics (e.g., usage level) of our customers to account for possible intrinsic similarities in taste.

Simultaneity or reflection. In the case of simultaneity or reflection (Manski 1993), a neighbor's defection affects the focal customer's defection, and at the same time the focal customer's defection affects the neighbor's defection. Following Barrot et al. (2008), we confront this problem as follows: First, we use the exact dates of defections. For modeling purposes, we aggregate the data to the monthly level, but we consider a customer's exposure to defection only if the neighbor's defection occurred before the focal customer's defection (at a daily resolution). Second, we use several lagged variables representing the exposure effect over time because it is not reasonable to assume that such simultaneity will last over several time periods. Counting a family defection as one defection also helps in this regard.

Response to an external shock. The potential bias of response to an external shock (De Paula 2009), also referred to as environmental conditions (Manski 2000), results from external factors in the market that cause customers to defect at a given time; for example, if another firm makes a competing offer, customers who find the offer appealing will defect at roughly the same time. A possible way to deal with such issues is to model the time until the event (e.g., defection) and not just whether the event occurs (Barrot et al. 2008). Thus, we model the exact date of defection and not just its occurrence. We assume that a sequence of defections among customers is less likely to result from correlated unobservables, because such unobservables should make customers defect at the same time rather than in a time gap. Thus, a sequence of defections suggests the existence of an additional influence mechanism. We further examine time dynamics using several lagged variables to represent the exposure effect over time.

Competitive effects may also play a role. That is, higher defection rates may be anticipated if a competitor advertises more (Rojas and Peterson 2008), especially because a high level of advertising may indicate significant promotional offers. From another angle, the focal firm's advertising may encourage current customers not to defect. Because multiple members of a social network may be exposed to the same advertising campaigns, one might wonder whether the effects witnessed could be partially explained by the level of competitive advertising activity. To examine this point, we obtained (from a firm that specializes in following advertising spending in this market) monthly data on the advertising spending of the three main players in the market. Consistent with the norms of advertising analysis in this market, we created a measure for each customer's exposure to advertising by multiplying the monthly spending by the published monthly advertising ratings of that customer's age and gender group (to reflect the difference in television viewership among age and gender groups). We took into account 16 groups (8 age groups $\times$ 2 gender groups), over the 12 months of 2008. Next, we incorporated the respective levels of exposure to firm advertising and competitor advertising into our social effects model (for the full analysis, see Part B of the Web Appendix at http://www.marketingpower.com/jmnov11). We saw little or no effect of advertising on the hazard of defection in this market. The effect of the other variables, including the social variables, on defection did not change, and the effect of advertising itself on the hazard of defection was very small.

Results

The data for the hazard models include information for 1,103,059 personal customers. We used information for 693,042 customers to estimate the models (due to missing values). Of this population, 28,102 customers defected from the cellular provider during 2008. These customers constitute 4.1% of the initial population; this proportion is consistent with published ranges of cellular churn rates in the country we investigated.

Table 1 presents the estimation results (using the PHREG procedure in SAS) for the traditional and the social models (Models 1 and 2, respectively). The direction of results in the traditional model is as expected: The hazard of defection increases with the number of service records, when usage goes down, and the more a person talks outside the network. The social variables added in the social model increase the fit of the model as reflected in both the Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC), which introduces a penalty term for the number of parameters in the model.

TABLE 1
Exposure to Defectors

Variable	Unit of Analysis	Model 1 Traditional Model: Parameter Estimate	Model 1 Traditional Model: Hazard Ratio	Model 2 Social Model: Parameter Estimate	Model 2 Social Model: Hazard Ratio
Exposure (first degree defections)	Number of defecting neighbors			.586 (.018)	1.797
Average tie strength with defecting neighbors	Percentage			.021 (<.001)	1.022
Average homophily with defecting neighbors	Percentage			.010 (<.001)	1.010
Average degree of defecting neighbors	Number			−.004 (<.001)	.996
Customer degree	Number of neighbors			.011 (.001)	1.011
Service records	Number of records	.033 (<.001)	1.033	.033 (<.001)	1.034
Delta use	Percentage	−.0001 (<.001)	.999	−.001 (<.001)	.999
Economic incentive	Percentage	−.073 (<.001)	.930	−.075 (<.001)	.928
Average monthly usage	Hours	.005 (<.001)	1.005	.0003 (<.001)	1.000
Time from enrollment	Years	−.023 (.001)	.978	−.023 (.002)	.977
Student	1 = Student	.023 (.027)	1.023	.005 (.027)	1.005
Sociodemographic Group 1	1 = Group member	−.289 (.028)	.749	−.452 (.028)	.682
Sociodemographic Group 2	1 = Group member	−.327 (.028)	.721	−.383 (.028)	.730
Sociodemographic Group 3	1 = Group member	.258 (.021)	.773	−.315 (.028)	.784
Age	Number of years	.003 (.009)	.940	.003 (<.001)	1.003
Gender	1 = Female	−.070 (.012)	.932	−.046 (.012)	.955
–2 LOG L		689,124		681,395	
AIC		689,146		681,427	
SBC		689,237		681,559	

Notes: All parameter estimates are significant at $p < .01$, except “Student” and “Age.”

The Extent of the Social Effect

The social model in Table 1 shows that exposure to defecting neighbors has a considerable effect on a customer’s hazard of defection, after controlling for a battery of variables that may affect retention. The model shows that each defecting neighbor is associated with an increase of 79.7% in the focal customer’s hazard of defection. It is useful to compare the magnitude of these results with published probabilities of social effect on adoption. We compared our results with findings from previous studies we were able to identify (almost all in the context of adoption) that examined the change in the probability (or hazard) of behavior due to exposure to the behavior of a social network neighbor (see Table W5 in Part C of the Web Appendix at http://www.marketingpower.com/jmnov11). The observed social effect on defection is as pronounced as that on adoption, which is consistent with findings regarding the choice of names for children (Berger and Le Mens 2009) and is even somewhat larger than reported effects from the adoption domain, with the exception of Hill, Provost, and Volinsky’s (2006) findings, which are outliers in terms of magnitude. The effects we observed are also somewhat larger than those reported in the case of quitting smoking.

The Predictive Power of the Model

A key interest of managers in the defection behavior of their customers is the ability to better predict defection (Neslin et al. 2006). A noteworthy question is whether the social variables help increase the predictive ability of churn models. Because the Cox regression we conducted does not allow us to examine predictive power, we tested this question using a parametric hazard model, using Weibull as the parametric specification of the baseline hazard (Srinivasan, Lilien, and Rangaswamy 2004). Note that one limitation of the parametric analysis is that, unlike the Cox semiparametric regression, it does not allow time-variant variables (Bowman 2004), which makes it less robust given the temporal effects in our data set. Therefore, using the parametric model for prediction purposes, we estimate the traditional and social models on a monthly basis.

We calculated the median survival time of each customer in each model, and the defection prediction is based on this median. For each model, we calculated the true positive rate—that is, the percentage of customers predicted to defect and actually defected—and the false positive rate—that is, the percentage of defection predictions that were found wrong.

Examining the bottom 1% of customers in terms of median survival time, we find that the social model raises the prediction ability of true positive from 20.5% in the traditional model to 28.1%, a relative increase of 37.5%. The social model also achieves a slight improvement over the traditional model in false positive rates. (For further details on the prediction procedure, see Part D of the Web Appendix at http://www.marketingpower.com/jmnov11.)

The Nature of the Social Process

Tie strength. With respect to average tie strength, we observe that at any given time, a 1% increase in a customer's average tie strength with defecting neighbors is associated with an increase of 2.2% in that customer's hazard of defection. For example, if a customer's average tie strength with defecting neighbors is 8% (which is approximately the average tie strength in our data), the customer's exposure to defecting neighbors is associated with an increase of 17.6% in the customer's defection hazard.

Homophily. We observe that every 1% increase in a customer's average homophily with defecting neighbors is associated with an increase of 1% in that customer's hazard of defection. For example, if a customer is exposed to the defection of a neighbor who has one attribute in common with the focal customer (i.e., the pair's homophily score is 25%), the exposure to this defecting neighbor is associated with a 25% increase in the customer's hazard of defection.

FIGURE 1
Average Tie Strength with Defecting Neighbors Versus the Defection Percentage

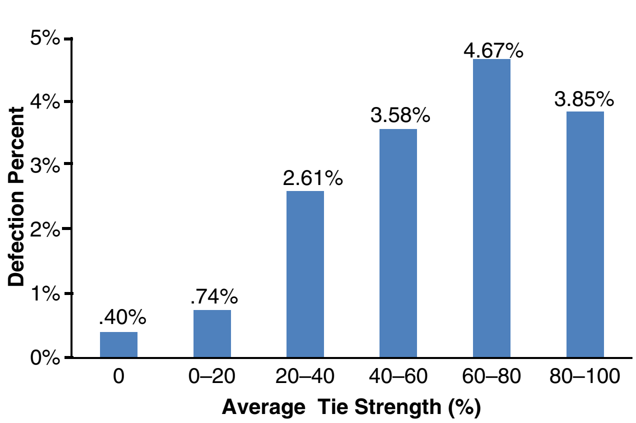
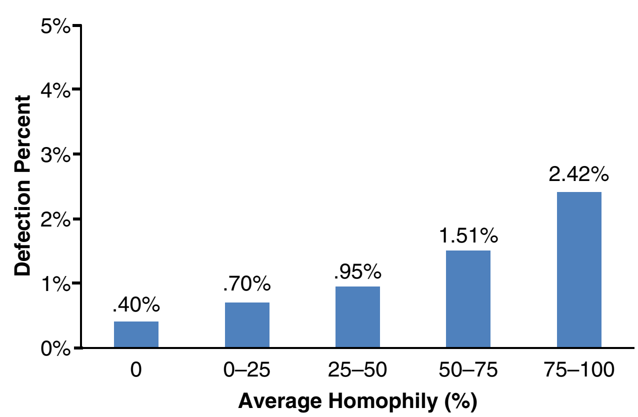


FIGURE 2
Average Homophily with Defecting Neighbors Versus the Defection Percentage



Figures 1 and 2 present these results from another angle: the percentages of defectors with respect to their various levels of average tie strength (Figure 1) and homophily (Figure 2) with defecting neighbors. (The level of similarity is measured in increments of 25% because it is a function of similarity across four demographic variables.) It is clear that in general, a customer's likelihood of defection following exposure increases as a function of average tie strength and of average homophily with defecting neighbors.

Economic incentive. We find that the ratio between the volume of within-network communication and the volume of out-of-network communication, which we associated with an economic incentive due to network externalities, affected the defection decision. The results indicate that a 1% decrease in the proportion of within-network communication is associated with a decrease of 7.2% in the hazard of defection (Model 2).

Focal customer's degree and average degree of defecting neighbors. We observe that each additional neighbor in a focal customer's local network is associated with an increase of 1.1% in that customer's hazard of defection. If we compare the average customer (whose degree is approximately 7) with the top 25% of customers (whose degree is greater than 10), we observe that being connected to three more neighbors is associated with an increase of 3.3% in the customer's hazard to defect. Note that we obtain this result when we control for the number of defectors in the social network of the focal customer. Moreover, we find that an increase of 1% in the average degree of defecting neighbors is associated with a decrease of .4% in the hazard of defection.

The exponential decline of effects over time. Table 2 presents the exposure model with lagging variables for five months (Model 3). We observe that the effect of a neighbor's defection on a focal customer's hazard of defection decreases exponentially over time (see also Figure 3), suggesting that as we move further away from the neighbor's defection event, the defection's effect on the focal customer's decision decreases.

TABLE 2
Social Influence Decrease over Time

Variable	Unit of Analysis	Model 3 Parameter Estimate	Model 3 Hazard Ratio
Exposure_t	Number of defecting neighbors at time t	.860 (.008)	2.364
Exposure_{t-1}	Number of defecting neighbors at time t − 1	.416 (.018)	1.516
Exposure_{t-2}	Number of defecting neighbors at time t − 2	.203 (.022)	1.225
Exposure_{t-3}	Number of defecting neighbors at time t − 3	.142 (.023)	1.152
Exposure_{t-4}	Number of defecting neighbors at time t − 4	.140 (.023)	1.150
Economic incentive	(%)	−.042 (<.001)	.959
Average monthly usage	(hours)	−.005 (<.001)	.995
Time from enrollment	(years)	−.025 (.002)	.975
Student	1 = Student	−.050 (.026)	.951
Sociodemographic Group 1	1 = Group member	−.392 (.023)	.676
Sociodemographic Group 2	1 = Group member	−.409 (.027)	.664
Sociodemographic Group 3	1 = Group member	−.199 (.020)	.820
Age	Number of years	.001 (.011)	1.001
Gender	1 = Female	−.039 (.012)	.962
−2 LOG L		743,755	
AIC		743,783	
SBC		743,899	

Notes: All parameter estimates are significant at $p < .01$, except "Student."

Customer Loyalty as a Moderator of the Social Effect

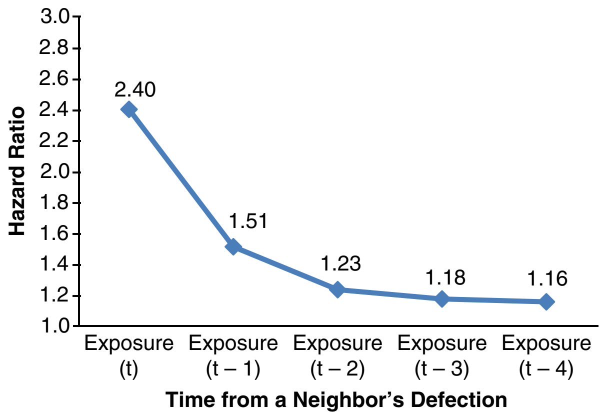
An additional analogy between the nonsocial and the social effects on retention involves the moderating effect of customer loyalty. Researchers have argued that loyal customers tend to defect less and to be less affected by service failures or by price increases (Srinivasan, Anderson, and Ponnavolu 2002). In a sense, loyalty can be viewed as immunity against environmental effects that might encourage defection. The question we ask is whether the same immunizing mechanism will be in effect among customers who are exposed to others' defections.

In the context of social interactions, prior research has considered the impact of customer loyalty on the effect of word-of-mouth interactions; such studies have mostly considered the loyalty of the *provider* of information. It has been suggested that a loyal, satisfied, and committed customer will tend to affect others more through word of mouth (De Matos and Rossi 2008). Here, we center on the *receiver* of information, who is exposed to the defection decisions of others. We may expect that the same characteristics that cause loyal customers to have a greater effect on others (De Matos and Rossi 2008) might also cause them to be *less* affected than nonloyal customers by information that stems from defecting neighbors.

Two widely used measures of loyalty in this regard are usage and customer tenure (Bolton 1998; Prins and Verhoef 2007). Heavy users of a given service, as well as tenured customers, may be less affected by information that stems from their neighbors compared with light users or new customers, respectively. One reason for this is that loyal customers may rely on their own rich experience when deciding whether to remain with a firm or defect. Another issue involves customer heterogeneity: Nonloyal customers would be expected to defect from a service earlier, and therefore, tenured customers are inherently more loyal (Fader and Hardie 2010).

To investigate the role of customer loyalty in the social effects on retention, we observed the hazard function over time for the groups that are more extreme in terms of usage and tenure, respectively. Figure 4 presents the estimated

FIGURE 3
Hazard Ratio as a Function of Time from the Neighbor's Defection



hazard ratios of the heaviest users (top 25% in terms of MOU and text messages) and the lightest users (bottom 25%) as functions of the amount of time following a neighbor's defection. Figure 5 presents the estimated hazard ratios for the highest tenured customers (top 25%; customers who stayed with the provider for seven years or more) compared with those of relatively new customers (bottom 25%; customers who stayed with the provider for two years or less).

Indeed, the hazard ratio curves of heavy users and tenured customers are clearly lower than those of light users and newer customers, respectively. We tested the difference between each pair of survival curves using the log-rank statistic of the Kaplan-Meier method (Allison 1995) and found it to be significant ($p < .001$). These results demonstrate the moderating role of customer loyalty in the social effects on retention: Loyal customers are less affected by negative information from their social network and are therefore even more likely to stay with the firm. The analysis done here enables us to quantify this underexplored phenomenon for the first time.

FIGURE 4
Hazard Ratio as a Function of Time from the Neighbor's Defection: Heavy Versus Light Users

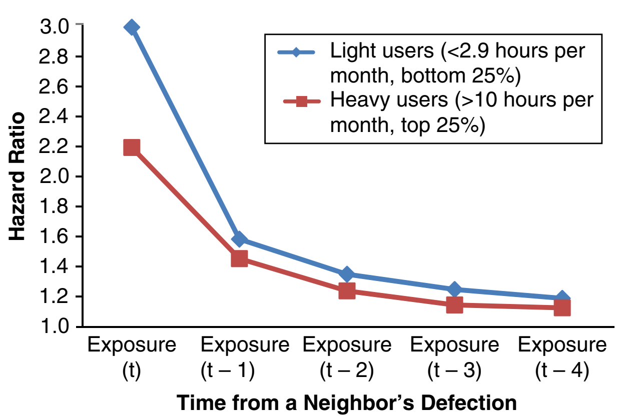
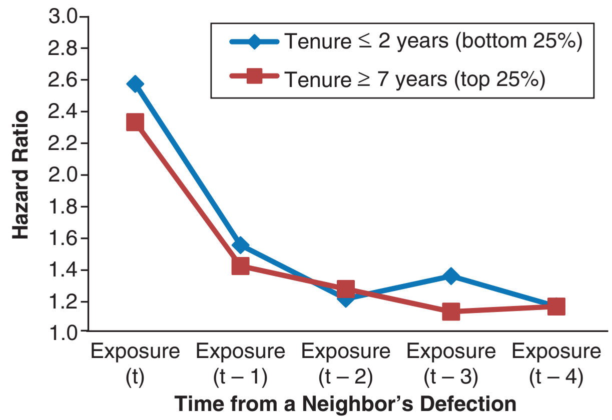


FIGURE 5
Hazard Ratio as a Function of Time from the Neighbor's Defection: Tenured Versus New Customers



Robustness Checks

Finally, in the course of building the model, we had to make some choices regarding the variable range and composition. To check the robustness of our findings, we estimated several variants of the social model (Model 2) and of the social model over time (Model 3) to determine whether the basic findings would remain similar.

First, we reestimated the social model (Model 2) using a different time interval for the main variables. Instead of using a monthly resolution (as used in Model 2), we chose a two-month resolution. Note that we cannot use a much larger window given the exponential decline over time in the social effect, demonstrated previously. Although, as expected, the hazard ratio for exposure decreased (from 1.79 to 1.47), in general, the value of other variables stayed the same. Regarding tie strength, we checked whether the absolute level of communication between two customers (i.e., the amount of time the focal customer spends talking with a given person) could be used as a measure of tie strength instead of the relative measure of communication that we originally adopted (i.e., the percentage of time the focal customer spends talking with a given person compared with the total amount of time he or she spends talking to customers in the network). We found that when we used the absolute value for communication volume, other variables stayed much the same, but tie strength itself became nonsignificant, which supports the relative approach we took. We also estimated a model that did not take into account exposure to defecting neighbors with whom the focal customer used to maintain weak ties, and we obtained similar results to the ones presented in Table 1 (Model 2). For homophily, another variable that may point to a similarity between customers, in addition to the ones we used, is customer tenure, because this may be related to the contractual obligations customers have. We found that adding similarity in tenure increased the effect of homophily itself on the hazard of defection, but it did not change the basic results in terms of the effects of other variables, including social variables such as exposure to defecting neighbors.

In addition, we conducted several other tests: We changed the exposure variable and, instead of looking at the number of defecting neighbors, used the cumulative number of defecting neighbors in a three-month-moving-window time frame. We also estimated the model for different segments, using segmentation based on age, usage, gender, tenure, and customer satisfaction. In all cases, in general, the results were consistent with those presented previously.

Discussion

Our results provide a consistent picture of how exposure to others' defections affects customers' defection decisions in the market we examined. We find that exposure to the attrition of network neighbors is associated with an increase in a customer's probability of defecting and that the effect is large: When controlling for various individual and social network factors, we observed that exposure to a defecting neighbor was associated with an increase of approximately 80% in a customer's probability of defection. These results are sizeable compared with reported probabilities that come mostly from the adoption domain. They clearly highlight the need for managers and researchers to study and understand the role of social effects in customer retention further.

A key question associated with the clustering of behavior in social networks is whether effects such as those we observed are indeed social effects. Recent research has suggested that many phenomena that are interpreted as social contagion effects may largely stem from homophily (Aral, Muchnik, and Sundararajan 2009). In the case of our study, it could be argued that people tend to be in social networks with people who resemble them, and because similar people with similar tastes may churn at the same time, the associated churn may be related to homophily and not to a social effect.

Indeed, the separation of homophily and communication effects is a significant challenge for network scholars. In this study, there are several indications that the hazard of defection is substantially influenced by social effects and not only by homophily. First, we controlled for homophily (through the demographic variables) and still observed a notable effect of exposure to defectors. Second, the exponential decay over time in the effect of a neighbor's defection suggests an effect that is more social in nature. It is not necessarily expected that such an effect would appear in the case of pure homophily. The significant effects of tie strength and of the economic incentive also point to the role of intercustomer communication in the defection decision.

The Nature of Social Effects on Retention

We find that the nature of defection-driven social effects is consistently similar to that reported in the domain of adoption. First, we find that a focal customer who has close ties with his or her defecting neighbors or is similar to them (in terms of personal characteristics) has a higher likelihood of defection.

We further witnessed an exponential decline over time in the exposure effect; the decline is rather rapid and is comparable to findings in the domain of adoption (Strang and Tuma 1993; Trusov, Bucklin, and Pauwels 2009). The similarity between the decline patterns in the cases of both adoption and attrition suggests that different types of social effects share similar dynamics (i.e., declining influence over time) and should encourage researchers to model and further explore the consequences of the social interaction carryover effect, as has been done for the advertising carryover effect (Tellis 2004).

We find that a customer with a higher degree (number of connections) has a greater likelihood of defecting. Note that we observe this effect after controlling for exposure to the number of defectors in the social network. Therefore, the effect cannot be attributed solely to the notion that higher-degree customers interact with more defectors. A possible explanation for this effect might be that, compared with customers with fewer connections, highly connected customers hear about more defections at higher degrees of separation.

Furthermore, an increase in the average degree of defecting neighbors is associated with a small decrease in the focal customer's hazard to defect. Recent research has highlighted the limited attention explanation (Katona, Zubcsek, and Sarvary 2011). This approach suggests that a person with a large number of social ties may be able to devote less attention to each tie, which eventually limits that person's level of influence on these ties. Thus, the level of attention a high-degree customer pays to his or her connections affects this customer's defection-related impact on each one.

These findings shed new light on the consequences of centrality in social networks. Often, high-degree customers are considered attractive customers because of their potential to affect others and also because their higher connectivity may lead to earlier exposure to innovations (Goldenberg et al. 2009). Our results suggest that greater connectivity may not mean greater influence and that there may even be a dark side of connectivity in the case of defections: Greater connectivity also means greater exposure to defectors and thus a greater chance of leaving. The trade-off between network hubs' greater influence and their greater risk of defection is a significant issue that should be pursued in further research.

Customer loyalty, which cannot be assessed in the case of new product adoption (because the customer has no prior relationship with the new product), has an effect on defection: We find that customers who are often labeled loyal (i.e., customers with higher tenure or who are heavier users) are less affected by others' defections. These results highlight an underexplored advantage of customer loyalty. For some time, loyalty was appreciated primarily for its contribution to customers' lifetime value (i.e., loyal customers were appreciated for providing higher profits for longer periods of time; Rust and Chung 2006). In addition, loyalty can contribute to customers' social value because retained customers influence others to adopt products through their social effects. Here, we observe a new aspect of the benefit of loyalty: It reduces a customer's tendency to be affected by others' defections.

Managerial Implications

A straightforward implication of our study is that firms should take customers' social networks into account when attempting to predict and manage customer churn. Recent research has demonstrated that the addition of network-related information to the commonly used geographic, demographic, and prior purchase data can substantially improve analysis of new product adoption (Hill, Provost, and Volinsky 2006). Our results suggest that this might also be the case for customer defections. This possibility is especially significant in light of our observation that advertising had no effect on defection. While advertising can certainly affect decision making in many markets, it seems that in mature markets such as the one we examined, customers' defection decisions are driven more by the customers' own experiences and by those of their social neighbors than by advertising. A reasonable alternative to some of the retention-geared advertising may be to invest in developing a better understanding of the behavioral drivers of retention, taking a broader social network perspective. For example, satisfaction surveys have traditionally focused on the individual; however, further examination of the satisfaction of friends, either by asking the focal customer or by independent surveys, might provide fruitful results.

A significant finding in this regard is the strength of mere exposure to defectors. Although specific properties associated with social relationships (e.g., tie strength, homophily) had differential effects on the defection decision, we observed that even when we controlled for these aspects, mere exposure to defectors had a relatively strong effect on the defection decision. An implication of this is that the absence of precise network-related information on defectors and their neighbors should not discourage firms from taking the social aspect into account: Mere exposure to a defection may be key piece of information on which to act.

Our results emphasize the urgency of managerial response to customer defections. In the case we examined, much of a defector's effect on his or her neighbors occurs during the two months after defection. If a firm aims to deal with the possible social influence of a defection, it should act swiftly, as soon as possible after the neighbor's defection event. Another issue is the need to consider network information when examining customer lifetime value (Rust and Chung 2006). In the context of new product adoption, previous research has indicated the additional value of customers who affect the adoption of others (Hogan, Lemon, and Libai 2003), and a similar analysis should be done in the context of social effects on retention.

The cellular industry offers researchers an almost unparalleled ability to study consumption behavior combined with social network information. To the extent possible, we have tried to avoid the use of industry-specific variables, and we believe that the fundamental results presented here are relevant for understanding social effects on customer retention. However, it is important to consider the extent to which the magnitude of the results presented here can be generalized for other industries. One issue to consider is that mobile phone services are characterized by relatively high customer involvement and possible normative pressure (Herbjørn, Pedersen, and Thorbjørnsen 2005). Markets with these characteristics, coupled with possible price-driven network effects, are likely to be associated with relatively strong social effects on attrition. Therefore, the effects found here may not be as strong in markets in which customer involvement is lower. Another issue is that the industry we examine serves as both a representation of the social network of customers and the product domain of defections. Because the cellular network enables the communications, we can expect that this service will be more frequently discussed in word-of-mouth communications than will other products. Consequently, we may witness greater social effects for mobile phone–related communication than for other products. From another angle, mobile phone services are often characterized by contractual agreements that curb the tendency of people to leave the service, even if they are influenced by others' word of mouth to do so. Lower switching costs in other markets may be associated with greater social effects on the retention decision.

The exact magnitude of the social effects on retention should thus be examined, when possible, for specific markets. Given the limited access to social network data, managers' ability to do so depends on the extent to which new technologies will enable the collection of more data on the social behavior of customers. One avenue might be to collect data through sources such as Facebook and other social networking sites. Another possibility is to take advantage of the emerging use of brand and online communities to better assess the relationship between social behavior and defection. Third-party providers that collect data from sources such as LinkedIn can also help in this regard.

Further Research and Limitations

Finally, some limitations of this study should be highlighted. The use of data from multiple industries and of products that are exogenous to the network (i.e., a product that is not the communication vehicle itself) can strengthen our knowledge of the magnitude of effects and the dynamics of social effects on retention. Additional information on customers' motivations to defect would have enabled us to distinguish the effects of the various defection types (e.g., active vs. passive defections). Furthermore, our data capture detailed information regarding customers' communication within a provider's network, as well as some information with respect to their overall communication habits. It would be beneficial, though challenging due to competition aspects, to capture a person's entire social network. Although there are research efforts in this direction (Eagle, Pentland, and Lazer 2009), the challenge of combining such data with real consumption decisions must still be overcome.

The cellular service market we examined in this study is a mature market, characterized by a high penetration rate. Because customers do not leave the category altogether but rather switch to a competing provider, it would be useful to consider the extent to which customers follow not only their neighbors' defection decisions but also their neighbors by choosing the same new provider. This requires data that are not available to us at this point.

Additional measures, such as the network distance between the focal customer and other potential influencers, could contribute to this study. In the context of public health (e.g., obesity), researchers have suggested that such influence takes place (Christakis and Fowler 2007); however, in the context of consumption decisions, second-degree influences have not been tested. This may be carried out by assessing the extent to which defections that happen two (and possibly three) degrees of separation from an individual affect his or her probability to defect. This analysis is significant but outside the scope of the current study.

Assessing the extent and nature of social processes involved in customers' decisions to defect is crucial to better understand, model, and eventually manage customer churn. Given that retention is central to firms' bottom line, we believe that further exploration of the social effects on customer retention will contribute to this promising line of research.

REFERENCES

Allison, Paul D. (1995), *Survival Analysis Using the SAS System: A Practical Guide*. Cary, NC: SAS Institute.

Aral, Sinan, Lev Muchnik, and Arun Sundararajan (2009), "Distinguishing Influence-Based Contagion from Homophily-Driven Diffusion in Dynamic Networks," *Proceedings of the National Academy of Sciences*, 106 (51), 21544–49.

Barabasi, Albert-Laszlo (2003), *Linked: How Everything Is Connected to Everything Else and What It Means*. New York: Plume Books.

Barrot, Christian, Arvind Rangaswamy, Sonke Albers, and Nazrul I. Shaikh (2008), "The Role of Spatial Proximity in the Adoption of a Digital Product," working paper, University of Kiel.

Baumann, Chris, Suzan Burton, and Greg Alliott (2005), "Determinants of Customer Loyalty and Share of Wallet in Retail Banking," *Journal of Financial Services Marketing*, 9 (3), 231–48.

Berger, Jonah and Gael Le Mens (2009), "How Adoption Speed Affects the Abandonment of Cultural Tastes," *Proceedings of the National Academy of Sciences*, 106 (20), 8146–50.

Bolton, Ruth N. (1998), "A Dynamic Model of the Duration of the Customer's Relationship with a Continuous Service Provider: The Role of Satisfaction," *Marketing Science*, 17 (1), 45–65.

——— and Katherine N. Lemon (1999), "Dynamic Model of Customers' Usage of Services: Usage as an Antecedent and Consequence of Satisfaction," *Journal of Consumer Research*, 36 (2), 171–86.

———, ———, and Matthew D. Bramlett (2006), "The Effect of Service Experiences over Time on a Supplier's Retention of Business Customers," *Marketing Science*, 52 (12), 1811–23.

———, ———, and Peter C. Verhoef (2004), "The Theoretical Underpinning of Customer Asset Management: A Framework and Propositions for Future Research," *Journal of the Academy of Marketing Science*, 32 (3), 271–92.

Bowman, Douglas (2004), "Survival Models for Marketing Strategy," in *Assessing Marketing Strategy Performance*, Christine Moorman and Donald R. Lehman, eds. Cambridge, MA: Marketing Science Institute, 115–44.

Brown, Jacqueline Johnson and Peter H. Reingen (1987), "Social Ties and Word-of-Mouth Referral Behavior," *Journal of Consumer Research*, 14 (3), 350–62.

Castilla, Emilio J. (2005), "Social Networks and Employee Performance in a Call Center," *American Journal of Sociology*, 110 (5), 1243–83.

Christakis, Nicholas A. and James H. Fowler (2007), "The Spread of Obesity in a Large Social Network over 32 Years," *New England Journal of Medicine*, 357 (4), 370–79.

——— and ——— (2008), "The Collective Dynamics of Smoking in a Large Social Network," *New England Journal of Medicine*, 355 (21), 2249–58.

——— and ——— (2009), *Connected*. New York: Hachette Book Group.

Cooil, Bruce, Timothy L. Keiningham , Lerzan Aksoy, and Michael Hsu (2007), "A Longitudinal Analysis of Customer Satisfaction and Share of Wallet: Investigating the Moderating Effect of Customer Characteristics," *Journal of Marketing*, 71 (January), 67–83.

De Matos, Ceslo Augusto and Carlos Alberto Vargas Rossi (2008), "Word-of-Mouth Communications in Marketing: A Meta-Analytic Review of the Antecedents and Moderators," *Journal of the Academy of Marketing Science*, 36 (4), 578–96.

De Paula, Aureo (2009), "Inference in a Synchronization Game with Social Interactions," *Journal of Econometrics*, 148 (1), 56–71.

Eagle, Nathan, A. Pentland, and D. Lazer (2009), "Inferring Social Network Structure Using Mobile Phone Data," *Proceedings of the National Academy of Sciences*, 106 (36), 15274–78.

Fader, Peter and Bruce Hardie (2010), "Customer-Base Valuation in a Contractual Setting: The Perils of Ignoring Heterogeneity," *Marketing Science*, 29 (1), 85–93.

Farrel, Joseph and Paul Klemperer (2007), "Coordination and Lock-in: Competition with Switching Costs and Network Effects," in *Handbook of Industrial Organization*, Vol. 3, Mark Armstrong and Robert Porter, eds. Amsterdam: North-Holland, 1967–2072.

Feick, Lawrence and Robin A. Higie (1992), "The Effects of Preference Heterogeneity and Source Characteristics on Ad Processing and Judgments about Endorsers," *Journal of Advertising*, 21 (2), 9–23.

Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science*, 23 (4), 545–60.

Goldenberg, Jacob, Sangman Han, Donald R. Lehmann, and Jae Weon Hong (2009), "The Role of Hubs in the Adoption Process," *Journal of Marketing*, 73 (March), 1–13.

———, Barak Libai, Sarit Moldovan, and Eitan Muller (2007), "The NPV of Bad News," *International Journal of Research in Marketing*, 24 (3), 186–200.

———, ———, and Eitan Muller (2010). "The Chilling Effects of Network Externalities," *International Journal of Research in Marketing*, 27 (1), 4–15.

Gupta, Sunil, Dominique Hanssens, Bruce Hardie, Wiliam Kahn, V. Kumar, Nathaniel Lin, et al. (2006), "Modeling Customer Lifetime Value," *Journal of Service Research*, 9 (2), 139–55.

Gustafsson, Anders, Michael D. Johnson, and Inger Roos (2005), "The Effects of Customer Satisfaction, Relationship Commitment Dimensions, and Triggers on Customer Retention," *Journal of Marketing*, 69 (October), 210–18.

Hartmann, Wesley R., Puneet Manchande, Harikesh Nair, Metthew Bothner, Peter Dodds, David Godes, et al. (2008), "Modeling Social Interactions: Identification, Empirical Methods and Policy Implications," *Marketing Letters*, 19 (3/4), 287–304.

Helsen, Kristiaan and David C. Schmittlein (1993), "Analyzing Duration Times in Marketing: Evidence for the Effectiveness of Hazard Rate Models," *Marketing Science*, 11 (4), 395–414.

Herbjørn, Nysveen, Per E. Pedersen, and Helge Thorbjørnsen (2005), "Intentions to Use Mobile Services: Antecedents and Cross-Service Comparisons," *Journal of the Academy of Marketing Science*, 33 (3), 330–46.

Hill, Shawndra, Foster Provost, and Chris Volinsky (2006), "Network-Based Marketing: Identifying Likely Adopters via Consumer Networks," *Statistical Science*, 21 (2), 256–76.
Hogan, John E., Katherine N. Lemon, and Barak Libai (2003), "What Is the Real Value of a Lost Customer?" *Journal of Service Research*, 5 (3), 196–208.
Katona, Zsolt, Peter Pal Zubcsek, and Miklos Sarvary (2011), "Network Effects and Personal Influences: The Diffusion of an Online Social Network," *Journal of Marketing Research*, 48 (June), 425–43.
Keller, Ed and Jon Berry (2003), *The Influentials*. New York: The Free Press.
Kleinbaum, David G. and Mitchel Klein (2005), *Survival Analysis: A Self-Learning Text*. New York: Springer.
Landsman, Vardit and Moshe Givon (2010), "The Diffusion of a New Service: Combining Service Consideration and Brand Choice," *Quantitative Marketing and Economics*, 66 (1), 1–14.
Lemon, Katherine N., Tiffany Barnett-White, and Russell S. Winer (2002), "Dynamic Customer Relationship Management: Incorporating Future Considerations into the Service Retention Decision," *Journal of Marketing*, 8 (January), 91–121.
Libai, Barak, Eitan Muller, and Renana Peres (2009), "The Role of Within-Brand and Cross-Brand Communications in Competitive Growth," *Journal of Marketing*, 73 (May), 19–34.
Manchanda, Puneet, Ying Xie, and Nara Youn (2008), "The Role of Targeted Communication and Contagion in Product Adoption," *Marketing Science*, 27 (6), 961–76.
Manski, Charles F. (1993), "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60 (3), 531–42.
——— (2000), "Economic Analysis of Social Interactions," *Journal of Economic Perspectives*, 14 (3), 115–36.
Mittal, Vikas and Wagner A. Kamakura (2001), "Satisfaction, Repurchase Intent, and Repurchase Behavior: Investigating the Moderating Effect of Customer Characteristics," *Journal of Marketing Research*, 38 (February), 19–34.
Monge, Peter R. and Noshir S. Contractor (2003), *Theories of Communication Networks*. New York: Oxford University Press.
Nair, Harikesh, Puneet Manchanda, and Tulikaa Bhatia (2010), "Asymmetric Peer Effects in Physician Prescription Behavior: The Role of Opinion Leaders," *Journal of Marketing Research*, 47 (October), 883–95.
Nam, Sungjoon, Puneet Manchanda, and Pradeep K. Chintagunta (2010), "The Effect of Signal Quality and Contiguous Word of Mouth on Customer Acquisition for a Video-On-Demand Service," *Marketing Science*, 29 (4), 690–700.
Neslin, Scott A., Sunil Gupta, Wagner Kamakura, Junxiang Lu, and Charlotte H. Mason (2006), "Defection Detection: Measuring and Understanding the Predictive Accuracy of Customer Churn Models," *Journal of Marketing Research*, 43 (May), 204–211.
Oliver, Richard L. (2009), *Satisfaction: A Behavioral Perspective on the Consumer*. New York: M.E. Sharpe.
Onnela, J.-P., J. Saramaki, J. Hyvonen, G. Szabo, D. Lazer, K. Kashi, et al. (2007), "Structure and Tie Strength in Mobile Communication Networks," *Proceedings of the National Academy of Sciences*, 104 (18), 7332–36.
Peres, Renana, Eitan Muller, and Vijay Mahajan (2010), "Innovation Diffusion and New Product Growth Models: A Critical Review and Research Directions," *International Journal of Research in Marketing*, 27 (2), 91–106.
Prins, Remco and Peter C. Verhoef (2007), "Marketing Communication Drivers of Adoption Timing of a New E-Service Among Existing Customers," *Journal of Marketing*, 71 (April), 169–83.
Reinartz, Werner and V. Kumar (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration," *Journal of Marketing*, 67 (January), 77–99.
Reingen, Peter H. and Jerome B. Kernan (1986), "Analysis of Referral Networks in Marketing: Methods and Illustration," *Journal of Marketing Research*, 23 (November), 370–78.
Rogers, Everett M. (2003), *Diffusion of Innovations*. New York: The Free Press.
Rojas, Christian and Everett B. Peterson (2008), "Demand for Differentiated Products: Price and Advertising Evidence from the U.S. Beer Market," *International Journal of Industrial Organization*, 26 (1), 288–307.
Rust, Roland T. and Tuck Siong Chung (2006), "Marketing Models of Service and Relationships," *Marketing Science*, 25 (6), 560–80.
———, Katherine N. Lemon, and Valerie Zeithaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy," *Journal of Marketing*, 68 (January), 109–127.
Ryan, Bryce and Neal C. Gross (1943), "The Diffusion of Hybrid Seed Corn in Two Iowa Communities," *Rural Sociology*, 8 (1), 15–24.
Ryu, Gangseog and Lawrence Feick (2007), "A Penny for Your Thoughts: Referral Reward Programs and Referral Likelihood," *Journal of Marketing*, 71 (January), 84–94.
Srinivasan, Raji, Gary L. Lilien, and Arvind Rangaswamy (2004), "First In, First Out? The Effects of Network Externalities on Pioneer Survival," *Journal of Marketing*, 68 (January), 41–58.
Srinivasan, Srini S., Rolph Anderson, and Kishore Ponnavolu (2002), "Customer Loyalty in E-Commerce: An Exploration of its Antecedents and Consequences," *Journal of Retailing*, 78 (1), 41–50.
Strang, David and Nancy Brandon Tuma (1993), "Spatial and Temporal Heterogeneity in Diffusion," *American Journal of Sociology*, 99 (3), 614–39.
Tellis, Gerard J. (2004), *Effective Advertising: Understanding When, How, and Why Advertising Works*. London: Sage Publications.
Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing*, 73 (September), 90–102.
Van den Bulte, Christophe and Iyengar, Raghuram (2011), "Tricked by Truncation: Spurious Duration Dependence and Social Contagion in Hazard Models," *Marketing Science*, 30 (2), 233–48.
——— and Garry L. Lilien (2001), "Medical Innovation Revisited: Social Contagion Versus Marketing Effort," *The American Journal of Sociology*, 106 (5), 1409–1435.
——— and Stefan Stremersch (2004), "Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test," *Marketing Science*, 23 (4), 530–44.
——— and Stefan Wuyts (2007), *Social Networks and Marketing*. Cambridge, MA: Marketing Science Institute.
Verhoef, Peter C. (2003), "Understanding the Effect of Customer Relationship Management Efforts on Customer Retention and Customer Share Development," *Journal of Marketing*, 67 (July), 30–45.
Villanueva, Julian and Dominique M. Hanssens (2007), "Customer Equity: Measurement, Management and Research Opportunities," *Foundations and Trends in Marketing*, 1 (1), 1–95.
Wangenheim, V. Florian (2005), "Postswitching Negative Word of Mouth," *Journal of Service Research*, 8 (1), 67–78.