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Social Effects on Customer Retention

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Report Summary

Researchers recognize the role that social interaction has in the adoption of new products or services: word-of-mouth interactions can lessen the risk and uncertainty associated with new products. But what about quitting behavior? If social connections can induce a person to adopt a product or service, can they also lead a person to abandon a product or service?

Until recently, it has been difficult to study this question because of the extensive data needed to do so, but in the past few years, researchers have used telecommunications databases to explore social network behavior. In the current research, Irit Nitzan and Barak Libai of Tel Aviv University use a cellular phone company's database of more than one million customers to examine the influence that customers who leave the company (defectors) have on their first-degree contacts (direct contacts, or "neighbors") in their social network.

Hypotheses

The researchers hypothesize that exposure to a defecting neighbor will increase a customer's likelihood of defecting and that factors of closeness and distance will moderate that effect. That is, the more closely the customer and the defecting neighbor are linked—and the more similar they are to each other—the greater the likelihood of defection becomes. The researchers also expect temporal distance to play a role: they predict that as time passes, the effect of the neighbor's defection will lessen. Finally, they expect that the more loyal the focal customer is to the company, the weaker the influence of his or her neighbor's defection will be.

Results

The researchers use a proportional-hazard model (commonly used to model the duration of customer-provider relationships) to examine the variables of exposure to defection, tie strength, similarity, and economic incentives. As they predict, the defection of a network neighbor increases a customer's hazard of defecting—in fact, it greatly increases it: exposure to a defecting neighbor is associated with an increase in the focal customer's hazard of defecting as much as 150%, or by 80% when tie strength and similarity (homophily) are controlled for.

The analysis shows that every 1% increase in a customer's tie strength with defecting neighbors is associated with a 2% increase in that customer's hazard of defection. The average tie strength of the customers in the data set is around 8%, which means that exposure to defecting neighbors increases their risk of defection by 16%. Similarity (homophily) among neighbors also increases the risk: a 1% increase in similarity between a customer and a defecting neighbor is associated with a 1.1% increase in the customer's hazard of defection.

As predicted, the influence of a neighbor's defection decreases markedly with the passage of time, and a customer's loyalty "immunizes" him or her against the effects of a defecting neighbor.

Implications

Given that mere exposure to a defecting neighbor is associated with an increase in a customer's hazard of defection by 80%, both managers and researchers have a strong incentive to understand the role of social effects in customer retention. This is especially true given that previous research has noted that negative events can have a more powerful effect on people than positive ones.

The researchers recommend that managers include customers' social networks in their attempts to predict and manage customer churn. Companies that are interested in understanding the behavioral drivers of retention should probably also take social networks into consideration. For example, customer satisfaction surveys might be modified to include questions regarding customers' friends who also use or have used the product or service in question.

The results also reinforce the importance of customer loyalty, as those customers who feel loyal to the company are less likely to be swayed by the defections of others. The researchers urge further study in other industries to confirm the generalizability of the findings. The current research examines the influence of first-degree contacts, but the researchers also recommend investigating the influence of defections of network members that are second-degree or even more greatly removed from the focal customer.

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Introduction

It has been acknowledged for a while that the adoption of new behaviors or innovations may be substantially affected by social interactions with others (Rogers 2003; Ryan and Gross 1943). Across a number of disciplines there is a growing realization that *quitting* behavior may be socially affected as well. For example, it has been 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. In the last 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 customers' 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, especially in the context of the adoption of new products, rather than on customer retention.

The role of social ties in the adoption of new products is largely accepted: information supplied through the word of mouth of social connections may mitigate the risk and uncertainty associated with new products (Rogers 2003). In the context of defection, however, customers' motivation to rely on word of mouth may be weaker, as they can build on their own experiences. Furthermore, in some cases, moving to a similar brand may not seem risky. Therefore, although intuitively there are good reasons to believe that a customer's choice to leave a firm might be affected by social factors, the nature of the role that social information plays in the defection (or retention) process has yet to be explored.

One of the reasons for our lack of knowledge on this issue relates to the extensive data needed to fully explore social effects on customer retention. In order to analyze such effects, researchers would ideally have longitudinal data on customers' purchase behavior, as well as on their social connections with other customers of the firm. Until recently such data were not accessible. The growth in customer relationship management (CRM) databases and the recently growing ability of firms to explore the social connections of their customer bases create new opportunities towards a better understanding of this important issue.

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 increasingly use 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). Our database includes information for all post-paid, personal customers (as opposed to multi-user business accounts) of the company over the course one year. Using data on the communication among those 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, we avoid the non-trivial 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 past defections by others in his or her social network. Using a proportional hazard model, we assess social effects on individuals' defection behavior and investigate how various characteristics and social connections of customers affect attrition. We refer to the immediate (first degree) members of each customer's social network, which we label *neighbors*, as the source of such social effects.

Three types of 'distance' measures are addressed: *Relationship distance*, which refers to the degree to which two people maintain a close interaction, *Similarity distance*, which refers to the degree to which two individuals are similar in their personal characteristics and *Time distance*, which refers to the effect over time of one's exposure to a defection event. We also show how *customer loyalty* may moderate the tendency to be affected by the defection of others.

Our main findings include the following:

The substantial role of exposure to defectors. Defection is not only a social phenomenon, but may also be a notable one. We found that prior to their defection; defecting customers in our cellular dataset were exposed to two times more defecting neighbors (direct, first-degree contacts) than were non-defecting customers. Using the survival analysis model we see that a neighbor's defection can increase the hazard of a focal customer's defection by up to 150%; and that even when controlling for the characteristics of the defecting customer , his purchase behavior and social ties with others, the mere exposure to another defector in the last month increases defection probability by 80%.

The moderating role of distance. Looking at distance among defectors we show the sizeable effect on defection of both *Relationship distance*, which refers to the tie strength or the degree to which two people maintain a close interaction ; and *Similarity distance*, which refers to the homophily or degree to which two individuals are similar in their personal characteristics. We further show that the effect of *time distance* between the defection events is evident, and that it decays exponentially with time, as in our case most of the effect had been in the two month since the neighbor's defection.

The moderating role of customer loyalty. We see that customer loyalty can serve to "immune" customers against the effect of others' defection. Heavy users and higher tenured customers were significantly less affected by neighbors' defections than light users and newer customers, respectively.

Retention and Social Effects

Background

The importance of customer retention stems mainly from its close connection to a firm's bottom line (Gupta and Zeithaml 2006; 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, researchers generally agree on the importance of retention as a key driver of a firm's profitability, and retention 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 towards building predictive models of customer churn (Neslin et al 2006).

Numerous studies have attempted to examine retention drivers. Among the studied drivers are customer satisfaction (Bolton, Lemon and Bramlett 2006), customer knowledge (Capraro, Bronarczyk and Srivastava 2003; Iyengar, Ansari, and Gupta 2007), current and expected switching costs (Lemon, Barnett-White and Winer 2002), product assortment (Borle et al. 2005), and various personal characteristics (Mittal and Kamakura 2001). In light of such studies, the absence of research on social influence as a defection driver is evident, especially given strong findings from the diffusion-of-innovation domain, where social influence has been established to have a notable effect on one's adoption decision (Keller and Berry 2003; Muller, Peres and Mahajan 2009; Van den Bulte and Wuyts 2007).

The Effect of Social Influence

Social influence may stem from the transmission of various pieces of information among people who are socially connected to one another. This transmission can be manifested through a variety of interactions a person has with others in his or her social circle. For example, an individual may receive information about a product by seeing another person with the product, by talking to another person about the product (Word-of-Mouth), or by receiving third-party information on another person who uses the product. Social influence can occur through the transmission of information that reduces uncertainty and search effort, normative and social pressure, or a result of network externalities (Muller, Peres and Mahajan 2009; Van den Bulte and Lilien 2001).

Our aim is thus to see if we can find indications for the social effects of customer defections on others' defections. Specifically, we suggest that in the context of the effect of a neighbor's previous defection on current defection, there are three key factors that play a role (See Figure 1, following References): Social distance, event distance and individual customer situation.

Social distance

While people may be affected by the entire social system they are part of, a person's close social network often plays a major role in his or her purchase decisions (Godes and Mayzlin 2004; Van den Bulte and Wuyts 2007). A convenient way to analyze social influences within the social network is to consider the *social distance* between two individuals (Bogardus 1933). The "closer" are two people the higher the chance they will affect each other. Following previous research we focus on two factors that drive social distance:

Relationship Distance. Past studies have indicated that individuals 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. Relationship distance may be represented by the *strength of tie* which signifies the intensity and tightness of a social relationship (Van den Bulte and Wuyts 2007), and was found to influence referral behavior among social contacts (Brown and Reingen 1987; Ryu and Feick 2007; Wuyts et al. 2004). Relationships may range from strong, primary relationships (such as spouse or close friend) to weak, secondary relationships (such as seldom-contacted acquaintances (Reingen and Kernan 1986).

Similarity Distance. Another determinant of adoption influence refers to the degree to which individuals are similar in their personal attributes. It has been 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 fact that customers are more likely to trust the endorsements of people whose preferences they share, and conversely, 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 individuals who take part in a social tie, that is how distant they are in respect to their personal attributes.

Event distance

Social network research has traditionally focused on the relationships (and distance) between entities (nodes) in a given social system (Barabasi 2003; Brown and Reingen 1987). Customer consumption analysis has largely looked at the distance between events, such as customer acquisition and retention (Bolton 1998; Dekimpe and Hanssens 1995). In our case there are two events of interest: neighbors' previous defections and the customer's current one. Thus, beyond any social distance between the individuals, we can expect that the time gap between the events will moderate the effect. Specifically we look at *Time Distance,* which refers to the time that passed between the two events. The carryover effects of some marketing actions such as advertising had been shown to decrease in an exponential manner (Tellis 2004), and there is some evidence to support a similar decay pattern in the context of word of mouth (Strang and Tuma 1993; Trusov, Bucklin and Pauwels 2009).

There are several reasons why the time distance from an event may drive decay of the social effect. One possibility is that people tend to discount information regarding more distant events, as it seems less relevant. Another reason may relate to the way the distant event is described by the defecting neighbor or perceived by the focal customer. For example, construal theory (Trope and Liberman 2003) suggests that the greater the temporal distance from an event, the more likely that the event will be represented in terms of a few abstract features that convey the perceived essence of the event (high-level construals) rather than in terms of more concrete and incidental details of the event (low-level construals). Low-level construal can thus better facilitate concrete consumption decisions. While most literature on construal looks at the effects of future events, some research suggests that these generalizations operate similarly for distance from both future and past events (D'Argembeau and Van der Linden 2004). Thus, we may expect that the effect of past defection will gradually decay over time as well.

Note there that there may be other types of distances that affect event distance but time. For example, the effect of a defection from a similar brand, or in a similar place may depend on the level of similarly. However in our empirical analysis we do not deal with such effects since we consider the same brand for all customers.

Individual customer situation.

Beyond the relationship with other neighbors and their events, a host of factors may impact the social effect on consumption. Some effects, may be situational, relate to the specific characteristics of the participants (for example how they tend to be influenced by others), or the types of the product in question (Muller, Peres and Mahajan 2009; Rogers 2003; Rosen 2009). While we will consider some demographic data we have as a control data, we do not focus here on the possible effect of demographic characteristics. Instead we focus on what we see as a possibly important moderator of social effect on retention- customer relationship with the service provider, which we generally label the effect of 'customer loyalty'.

Past research has considered the impact of customer loyalty on the effect of word of mouth interactions, mostly looking at the loyalty of the provider of information. It had been suggested that loyal, satisfied and committed customer will tend to affect others more via word of mouth (de Matos and Rossi 2008). Here, we center on the receiver of information, who observers the defection decision of others. Applying the same logic of why loyal customers will tend to affect more via positive word of mouth (de Matos and Rossi 2008) we expect that loyal customers will be less affected than ‘non-loyal’ customers by information that stems from defecting neighbors.

Many measures have been used to represent customer loyalty; two central ones among them are *usage* and *customer tenure* (Bolton 1998). We expect that heavy users of a given service, as well as tenured customers, will be less affected by information that stems from their neighbors, when compared to light users or to new customers, respectively. One reason for the expected moderated effect of such social information stems from the assumption that loyal customers would rely on their own rich experience when deciding whether to remain with a firm or defect. Another issue relates to customer heterogeneity; non-loyal customers would be expected to defect from a service earlier; therefore tenured customers are inherently more loyal (Fader and Hardie 2010).

Note that in addition to “real loyalty” which is based on attitude towards the brand, we may capture here also “spurious loyalty” which reflects ones tendency for repeat patronage behavior due to switching costs (Dick and Basu 1994). However this does not change the basic direction of the effect, as spurious loyalty can be expected to operate as a moderating variable in a similar manner to real loyalty.

Propositions

Our aim is to examine the potential social effects of the different kinds of social distance on defection. We examine data on customers of a service provider and evaluate the distances between each pair of customers in this social network, as well as the distances between defection events that occur within the network. We approach this goal by investigating a specific product category: cellular telephone services. We focus on the cellular 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). On the other hand, while churn in this industry is a key managerial variable, applied churn models typically do not incorporate such social aspects.

The extent to which social effects should affect defection in contemporary cellular markets is not immediately clear. By 2008, when the data for this empirical study were logged, the industry was mature, and the risk reduction that characterized the industry's social effects in its earlier days had probably decreased substantially. It could be argued that nowadays customers may be affected more by promotion, level of service and switching costs associated with their contracts. On the other hand, there are increasing indications that social ties play a principal role in people's decisions across many aspects of their lives (Christakis and Fowler 2009; Wuyts et al 2010; Rosen 2009). Defection from a company may often be associated with considerable risk, especially as the alternative is not always clear. Additionally, negative word of mouth generated after defection may drive further defections (Wangenheim 2005), especially given the possibly disproportional effect of negative word of mouth compared with positive word of mouth (Goldenberg et al 2007).

We summarize our expectations on the social role of customer defections in the following propositions:

Proposition 1: ***Exposure.*** *A customer's exposure to a defecting neighbor in his or her close social network will increase the probability that the focal customer will defect.*

Proposition 2: ***Tie strength.*** *The stronger the focal customer's relationship with a defecting neighbor, the higher the former's hazard of defection, following the latter's defection.*

Proposition 3: ***Homophily****. The greater the homophily of a focal customer to a defecting neighbor, the greater the contribution of the latter's defection to the former's hazard of defection.*

Proposition 4: ***Time distance****. The influence of a defecting neighbor in one's social network on one's decision to defect decreases over time (as the relevant defection event grows further away).*

Proposition 5: ***Loyalty.*** *'Loyal' customers are less likely to defect following a neighbor's defection, compared with 'non-loyal' customers.*

> *Proposition 5a:* ***Usage level****. The greater the usage of a focal customer, the lower his or her hazard of defection following exposure to a defecting neighbor.*
>
> *Proposition 5b:* ***Tenure****. The greater the tenure of a focal customer with the firm, the lower his or her hazard of defection following exposure to a defecting neighbor.*

Data

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 no uncovered areas, so it can be assumed that all the customers of this provider experienced the same level of service.

The communication behavior of all personal customers of one cellular provider in this country (approximately 1.1 million customers) over 2008 was tracked in the dataset. The research focuses on personal post-paid 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 a cellular provider, which enabled us to construct a complete social network. We did not have access to detailed communication beyond the provider's network; however, the total number of MOU and SMSs (a SMS is considered one minute of talk for this study) is captured. We also had access to four socio-demographic characteristics of the provider's customers: gender, age, segment, and socioeconomic status (taken from zip code database), as well as information regarding the date in which the customers joined this provider's service (and hence their tenure). In order to protect customers' privacy, each phone number was encrypted in a way that still enabled us to track that number through the entire research dataset.

In some countries, mobile service providers' pricing policies (charging for incoming calls as well as outgoing calls) which may lead to skewed data toward trusted interactions only. This is not an issue in the current study, since payments in this country are for outgoing calls only. Additionally, the monthly bill is based on actual minutes of use and not on pre-purchased minute blocks as is widely used in the US.

The cellular communication industry had been historically characterized by a pricing-driven network effect (Farrel and Klemperer 2006). 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 firm, while 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.

We used three months of communication data between the customers to reconstruct each customer's social network within the provider's network (Onnela et al. 2007). This is the 'base map', and it is comprised of communication data from January to March 2008. The 1.1 million customers in the database conducted 49.6 million calls and exchanged 12.7 million SMSs within this 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 those customers). The network's clustering coefficient, which represents the clustering level of the social network (neighbors' tendencies to communicate with one another), is 0.17, which is generally consistent with observations for reported social networks.

To determine a 'defection' we used the following criteria: the defection was either announced by the customer or determined according to the provider's definition of a defecting customer, which is consistent with industry standards (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 also attributed to family plans in which a family gets a lower rate for within-family calls. However, in our case whenever a family moves to another supplier at the same time, we count it as one defection.

As seen in Figure 2 (following References), most customers (66.0%) in our dataset were not exposed to any defecting neighbors in their immediate networks in 2008; about 22% of the customers were exposed to one neighbor who defected, and so on.

Methodology

Marketing researchers often study the time that passes until an event occurs (e.g., the duration of the customer–provider relationship, time from a product's introduction to its adoption, or time between consecutive household purchases). Survival analysis techniques are widely used in marketing to study various event occurrences that relate 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 widely used by researchers to model the duration of the customer–provider relationship as well as the probability of a customer's ending it (Bowman 2004; Rust and Chung 2006). 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 5.6% of the customers churned in the year analyzed, so right censoring is an issue to consider). Second, it has the capacity to analyze both time-constant independent variables (e.g., demography) and time-varying independent variables. Since variables such as exposure to defectors can change over time, 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 to be *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 be also considered here, since customers joined the service at different points in time. 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).

Following previous research (Bolton 1998; Reinartz and Kumar 2003), we use the semi-parametric partial likelihood estimation. This estimation allows 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). Since we used the Cox partial likelihood method, we handled tied data (events that occurred at the same time) by using the Efron approximation (1977).

Variables

Exposure. The exposure variable represents the presence of previous defectors in the social system of a customer (as noted above, we refer to immediate (first-degree) social system members as "neighbors" for simplicity). We considered exposure to defecting neighbors to be a time-varying variable and defined the exposure of customer *i* in month *t* as the following sum:

$$Exposure_{i,t} = \sum_{j \in SN_i} \delta_{j,t}$$

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: its value is 1 if customer *j* defected in month *t*, and 0 otherwise.

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

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. The tie strength (*TS*) between customer *i* and customer *j* from *i*'s perspective was calculated as follows:

$$TS_{i,j} = \frac{Comm\_vol_{i,j}}{Total\_comm_i}$$

where $Comm\_Vol_{i,j}$ 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*). $TotalComm_i$ is the total volume of communication that *i* conducted within this network.

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

$$avgTS_{i,t} = \frac{\sum_{j \in SN_i} TS_{i,j} * \delta_{j,t}}{\sum_{j \in SN_i} \delta_{j,t}}$$

where, as above, $\delta_{j,t}$ 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 *avgTS*=0.

Homophily. Following Brown and Reingen (1987), we measured customers' homophily as the percentage of similar characteristics they share. There are four socio-demographic characteristics in our data (gender, age, segment, socioeconomic status). To evaluate the homophily between any two customers, we assigned a score of 0.25 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). Similarity of gender, segment, and socio-economic status were measured with binary variables, and ages were determined 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*, *avgH* was calculated as follows:

$$avgH_{i,t} = \frac{\sum_{j \in SN_i} H_{i,j} * \delta_{j,t}}{\sum_{j \in SN_i} \delta_{j,t}}$$

Where, as above, 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 *avgH*=0. The term $H_{i,j}$ represents the level of homophily between the focal customer *i* and neighbor *j*.

Economic incentive. While differential pricing did not apply to over 80% of the users at the time of the study, it did apply to some customers. In addition one could wonder if some customers did not percive such a difference based on the past where it existed. It is thus interesting to see if a 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 variable that reflects the possible economic considerations of a given customer. The idea is to separate one'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 communication (within-network + out-of-network; denoted *Total_MOU*) is a variable we label Economic Incentive (EI).

$$EI_i = \frac{Within\_Network\_MOU_i}{Total\_MOU_i}$$

One can expect that a higher *EI* value for a given customer reflects a greater effect of network externalities, since a neighbor's defections will result in a greater economic loss to that customer.

Other variables. In addition to the above, we included in the hazard model the control variables that were available to us. These include usage, tenure (time with the supplier), and membership in several segments as identified by the supplier (gender, ethnic groups, students, young customers).

Tables 1a and 1b (following References) provide information about the variables used in this study.

Identification

The attempt to infer social influence from observational data raises questions of identification (Manski 2000, Hartmann et al 2008). 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*. In the appendix we specify how we attempted to mitigate the possible biases.

Results

Before introducing our formal model results, we present a ‘back-of-the-envelope’ demonstration of the relationship between customer’s defections and their exposure to previously defecting neighbors.

Figure 3 (following References) presents a comparison of defecting customers with customers who remained with the provider throughout 2008 in terms of the average number of defecting neighbors they were exposed to. On average, compared with non-defecting customers, defecting customers were exposed to more than twice as many defecting neighbors ($p<0.001$).

The data for the hazard models presented in Table 2 include information for 1,102,868 personal customers. We used information for 853,643 customers to estimate the models (due to some missing values). Out of this population 47,764 customers defected from the cellular provider during 2008. These customers constitute 5.6% of the initial population; this proportion is consistent with published ranges of cellular churn rates in this country.

We start by looking at the exposure effect and the effects of relationship and similarity distance. Table 2 includes three hazard models that enable us to see the marginal effects of the explanatory variables. In the first model we see the effect of mere exposure to defectors on the hazard of defection. In the second we take into account a number of control variables, yet without the relationship and similarity distance variables of tie strength and homophily with defectors. In the third we include also average tie strength and average homophily. From a managerial perspective, beyond the parameter estimate there is particular interest in the hazard ratio, which represents the increase in the probability of defection that is associated with a unit change in the specific parameter.

Table 2 yields several interesting observations, as follows:

Exposure matters, and quite a lot.

Consistent with Figure 3, Table 2 shows a considerable effect of exposure to defecting neighbors on a customer's hazard of defection. The extent of this effect depends on the degree to which we control for other variables (see model 1 versus model 2 and model 3), yet in all cases it is clearly considerable. When we consider only exposure (model 1), each additional defecting neighbor is associated with an increase of 135% in the focal customer's probability of defection. When we control for variables without incorporating relationship distance or similarity distance (model 2), the increase is about 150%. When tie strength and homophily variables are controlled for (model 3), each defecting neighbor is associated with an increase of 80% in the focal customer's hazard of defection. Each one of the models (1, 2 and 3) supports proposition 1.

Relationship and similarity distance variables matter as well.

Adding the relationship and similarity variables (model 3) contributes (though not dramatically) to the model fit (note that the fit using the measures at the bottom of Table 1 is better as the number is lower). With respect to average tie strength, we observe that at any given time, a 1% increase in the average tie strength with defecting neighbors is associated with an increase of 2% in the 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), then the customer's exposure to defecting neighbors is associated with an increase of 16% in the customer's defection hazard. This finding supports proposition 2.

With respect to average homophily, we observe that every 1% increase in the average homophily with defecting neighbors is associated with an increase of 1.1% in the 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., their homophily score is 25%), the exposure to this defecting neighbor is associated with an increase of 27.5%,in the customer's hazard of defection, which gives support to proposition 3.

It is thus also reasonable to conclude that the decrease in the hazard ratio of *exposure*, from 2.511 in model 2 to 1.813 in model 3, can be attributed to the inclusion of these two variables (average tie strength and homophily) in the model.

To see these results from another angle, we present in Figures 4a and 4b (following References) the percentages of defectors with respect to their various levels of average tie strength (Fig. 4a) and homophily (Fig. 4b) 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 defection level following exposure generally increases as a function of average tie strength and of average homophily.

The effect of exposure decreases over time.

Our next analysis examines the effect over time of customers' exposure to defecting neighbors. Model 4 adds to the exposure variable in model 2 several lagging exposure variables (see Table 3). Exposure_{t-1} is 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. Table 3 (following References) presents the exposure model with lagging variables for five months (model 4). 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 5). This model's results support proposition 4.

Loyal customers are less likely to defect following a neighbor's defection.

Looking at the Tables 2 and 3 we see that as expected the effect of tenure is negative. The higher the tenure with the firm, the lower the customer's tendency to defect. The effect of usage is complex: At table 2 it is positive (contrary to expectation) yet relatively to other variables, the effect size is very small. At table 3, when looking at the dynamics over time, it is negative, and also of small magnitude. Indeed past research has pointed to the complexity of the effects of usage over time, which may introduce noise in usage analysis. For example, the relationship between payment equity and usage can affect its consequences, since usage serves both as an antecedent of future usage and as a consequence of customer satisfaction (Bolton and Lemon 1999). To be still able to explore the usage effect we considered the more discriminative segments - heavy users vs. light users.

Figure 6a presents the estimated hazard ratios of the heaviest users (top 25% in terms of MOU) and of the lightest users (bottom 25%) as functions of the time following a neighbor's defection. Figure 6b presents the estimated hazard ratios for the highest tenured customers (top 25%; customers who stayed with this provider for 7 years or more), compared to those of the relatively new customers (bottom 25%; customers who stayed with this provider for 2 years or less).

We indeed see that the hazard ratio curves of heavy users and of tenured customers are clearly lower than those of light users and of newer customers, respectively. The difference between each pair of survival curves was tested using the log-rank statistic of the Kaplan-Meier method (Allison 1995) and was found to be significant ($p<0.001$). These findings support propositions 5a and 5b.

Discussion

Using a large-scale cellular service database that captures the communication as well as the defection activity of customers, we were able to explore the social nature of customer attrition. We found that exposure to attrition of network neighbors was associated with a higher attrition probability of customers. We find the size of this effect intriguing. When controlling for various individual-level factors, which included relationship strength as well as similarity measures with previous defectors, we observed that mere exposure to a defecting neighbor was associated with an increase of 80% in a customer's probability of defection. These notable effects point to the need of managers and researchers to further study and understand the role of social effects in customer retention. In this section we will discuss our findings, consider managerial implications of our results, and discuss potential future avenues.

The nature of the social effect

Several fundamental questions arise in relation to the nature of the effect we identified. The first question may be whether the effect we observed is, in fact, a social effect. While behavioral association among network members is generally interpreted as a social effect, recent research (Aral, Muchnik and Sundararajan 2009) argues that many phenomena that are interpreted as social contagion effects may largely stem from homophily. In the case of our study, one might argue that people tend to be in social networks with people who resemble them, and since 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, because similar people may also communicate more among themselves, the separation of homophily and communication effects is a significant challenge for network scholars. Determining the precise role of each effect in a specific case, demands very rich datasets coupled with advanced research methods. In this study, while we did find that homophily with defectors played a role in the defection decision, there are several indications that the hazard of defection is largely 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 effect of tie strength and the economic incentive effect also point to the role of inter-customer communication in the defection decision.

Another question relates to the role of network externalities—in our case, an economic incentive due to pricing scheme—versus the more informational communication effect. Here, too, and similar to the case of adoption (Van den Bulte and Stremersch 2004), the separation is not trivial. In our database however, more than 80% of the subscribers do not have pricing based network externalities, so network externalities were probably not a main driver of a social defection effect. We did find that the ratio between in-network and out-of-network communication, which we associated with an economic incentive, does affect the defection decision. We see that a 1% decrease in the proportion of in-network communication is associated with a decrease of 5.55% in the hazard of defection (model 3). We note however, that after we control for this variable, the exposure effect we observed was still very large.

After all variables, including tie strength and homophily, are controlled for, the effect of exposure to defectors is still large: the hazard ratio is 1.8 (80% increase in probability). The size of the effect may relate to the nature of the negative information that is transmitted when one is exposed to a neighbor's defection. Previous researchers have largely agreed that the individual-level effects of negative word of mouth are larger than those of positive word of mouth (Goldenberg et al 2007). Thus, while adoption contagion effects may rely more on verbal communication, for negative effect the mere knowledge of defection may be more powerful.

Different kinds of distance

We found that in order to understand the social effect of defection, one needs to take into account different kinds of social distance. Tie strength and homophily (relationship distance and similarity distance, respectively) have been examined in previous studies, but typically separately. Given the rather limited correlation between these variables in our dataset (0.35), we see evidence in our results for the need to incorporate *both* variables to reflect the essence of social distance between neighbors.

In addition, the significant effect of time distance between the events, is noticeable. The exponential decline is rather fast, and is comparable to findings in the domain of adoption (Strang and Tuma 1993; Trusov, Bucklin and Pawels 2009). It will be interesting to study how different product and network properties can affect the pattern of this decline.

Managerial implications

A straightforward implication of our study is that firms should include customers' social networks 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 defection. Furthermore, firms that aim to better understand the behavioral drivers of retention may want to take a broader social network perspective. For example, satisfaction surveys have traditionally focused on the individual, yet further examination of the satisfaction of friends, either by asking the focal customer or by independent surveys, is a direction marketers may want to explore. As demonstrated here, the differential effects of different network distance measures should be taken into account.

Our results point to the urgency of managerial response to customer defection. In our case much of the effect is found in the two months after the neighbor's defection. If a firm aims to deal with this possible social influence, it should act fast, as close as possible to the neighbor's defection event.

Our results also highlight the need to consider network information when examining customer lifetime value (Rust and Chung 2005). In the context of new product adoption, previous research has pointed to the additional value of customers who affect the adoption of others (Hogan, Lemon and Libai 2003). Naturally, the social value of opinion leaders is expected to be higher in this regard (Libai, Muller and Peres 2010).

Finally, our result highlights another advantage of customer loyalty. For quite a while loyalty was appreciated primarily for its contribution to customers' lifetime value, i.e., long-term customers were appreciated for providing higher profits for longer periods of time. More recently, loyalty was found to contribute to customers' social value; loyal customers influence others to adopt products (Libai, Muller and Peres 2010). In this study we observe a new perspective of the benefit of loyalty: loyalty reduces a customer's tendency to be affected by the defection of others. Loyal customers are therefore 'immunized', to some extent, from undesired social effects.

Future Research and Limitations

We have mentioned a number of avenues for future research, and more should be acknowledged. In this study was we used data from the cellular industry, which served both as a representation of the social network of customers and as the product domain of defections. Data from other industries can help to evaluate the extent to which our results are category-dependent.

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, yet very challenging due to competition aspects, to capture one's entire social network. While there are research efforts in this direction (Eagle, Pentland, and

Lazer 2009), the challenge of combining them with real consumption decisions must still be overcome.

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

Additional distance measures, such as network distance, could contribute to this framework. In the context of public health (e.g., obesity) it is suggested that such influence takes place (Christakis and Fowler 2007); yet 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 occur two (and maybe three) degrees of separation from an individual affect his or her probability to defect. This is outside the scope of the current study.

Finally, one of the shortcomings of the semi-parametric proportional hazard model used in this research is the inability to produce forecasts using the models estimated, thereby limiting the ability to compare the models. Researchers who focus on predictions may want to use tools that are more restrictive in terms of theory-building yet are better suited for predictions, such as logistic regression or a parametric hazard model.

Appendix

Mitigating problems of identification

The estimated models' structure may lead to several identification problems, associated with inferring social influence from observation data about behaviors that are hypothesized to occur as a result of social influences. We dealt with this issue in a number of ways:

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 research incorporated into models 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, socio-demographic level) and usage characteristics (e.g. usage level) of our customers to account for possible intrinsic similarities in taste.

Response to an external 'shock' (de Paula 2009). This potential bias, 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, and not in a time gap. Thus, a sequence of defections suggests the existence of an additional influence mechanism. We further examine time dynamics by using several lagged variables to represent the exposure effect over time.

Simultaneity or *reflection* (Manski 1993). In this case, 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: (1) 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 *prior* to the focal customer's defection (at a daily resolution). (2) We use several lagged variables representing the exposure effect over time since 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.

References

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

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), 21544–21549.

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.

Bogardus, Emory S. (1933), "A Social Distance Scale," *Sociology & Social Research*, 17, 265–271.

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.

Bolton, Ruth N. and Katherine N. Lemon (1999), "A Dynamic Model of Customers' Usage of Services: Usage as an Antecedent and Consequence of Satisfaction," *Journal of Marketing Research*, 36 (May), 171-186.

Bolton, Ruth N., Katherine N. Lemon, and Matthew D. Bramlett (2006), "The Effect of Service Experiences over Time on a Supplier's Retention of Business Customers," *Marketing Science,* 52 (12), 1811–1823.

Bolton, Ruth N., Katherine N. Lemon, 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), 271–292.

Borle, Sharad, Peter Boatwright, Joseph B. Kadane, Joseph C. Nunes, and Galit Shmueli (2005), "The Effect of Product Assortment Changes on Customer Retention," *Marketing Science*, 24 (4), 616–622.

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, 115–144.

Brown, Jacqueline Johnson and Peter H. Reingen (1987), "Social Ties and Word-of-Mouth Referral Behavior," *Journal of Consumer Research*, 14 (3), 350–362.

Capraro, Anthony J., Susan Bronarczyk, and Rajendra K. Srivastava (2003), "Factors Influencing the Likelihood of Customer Defection: The Role of Consumer Knowledge," *Academy of Marketing Science*, 31 (2), 164–175.

Castilla, Emilio J. (2005), "Social Networks and Employee Performance in a Call Center," *American Journal of Sociology*, 110 (5), 1243–1283.

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, 370–379.

——— and ——— (2008), "The Collective Dynamics of Smoking in a Large Social Network," *New England Journal of Medicine*, 355, 2249–2258.

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

D'Argembeau, Arnaud and Martial Van der Linden (2004), "Phenomenal Characteristics Associated with Projecting Oneself Back into the Past and Forward into the Future: Influence of Valence and Temporal Distance," *Consciousness and Cognition*, 13 (4), 844–858.

Dekimpe, Marnik G. and Dominique M. Hanssens (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1–21.

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

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, 578–596.

Dick, Alan S. and Kunal Basu (1994), "Customer Loyalty: Toward an Integrated Conceptual Framework," *Journal of the Academy of Marketing Science*, 22(2), 99-113

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), 15274–15278.

Efron, Bradley (1977), "The Efficiency of Cox's Likelihood Function for Censored Data," *Journal of the American Statistical Association*, 76, 312–319.

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 (2006), “Coordination and Lock-in: Competition with Switching Costs and Network Effects,” working paper.

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), 545–560.

Goldenberg, Jacob, Barak Libai, and Eitan Muller (2010). “The Chilling Effects of Network Externalities,” *International Journal of Research in Marketing*, 27 (1), 4–15.

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

Gupta, Sunil, Dominique Hanssens, Bruce Hardie, Wiliam Kahn, V. Kumar, Nathaniel Lin, Nalini Ravishankar and S. Sriram (2006), “Modeling Customer Lifetime Value,” *Journal of Service Research*, 9 (2), 139–155.

——— and Valarie Zeithaml (2006), “Customer Metrics and Their Impact on Financial Performances,” *Marketing Science,* 25 (6), 718–739.

Hartmann, Wesley R., Puneet Manchande, Harikesh Nair, Metthew Bothner, Peter Dodds, David Godes, Kartik Hosanagar and Catherine Tucker (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.

Hill, Shawndra, Foster Provost, and Chris Volinsky (2006), "Network-based Marketing: Identifying Likely Adopters via Consumer Networks," *Statistical Science*, 21 (2), 256–276.

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.

Iyengar, Raghuram , Christophe Van den Bulte and Jeonghye Choi (2010), "Social Contagion in New Product Diffusion: Do Affiliation and Geography Capture Social Network Ties?," working paper.

Iyengar, Raghuram , Asim Ansari and Sunil Gupta (2007), "A Model of Consumer Learning for Service Quality and Usage," *Journal of Marketing Research*, 44 (4), 529-544.

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 (1), 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 (3), 19–34.

Libai, Barak, Eitan Muller, and Renana Peres (2010), "The Social Value of Word of Mouth Programs: Acceleration vs. Acquisition," working paper.

Manchanda, Puneet, Ying Xie, and Nara Youn (2008), "The Role of Targeted Communication and Contagion in Product Adoption," *Marketing Science*, 27 (6), 961–976.

Manski, Charles F. (1993), "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60, 531–542.

Manski, Charles F. (2000), "Economic Analysis of Social Interactions," *Journal of Economic Perspectives*, 14 (3), 131.

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 (1), 19–34.

Monge, Peter R. and Noshir S. Contractor (2003), *Theories of Communication Networks.* New York: Oxford University Press.

Muller, Eitan, Renana Peres, and Vijay Mahajan (2009), "Innovation Diffusion and New Product Growth Models: A Critical Review and Research Directions," *International Journal of Research in Marketing*, *forthcoming*.

Nair, Harikesh, Puneet Manchanda, and Tulikaa Bhatia (2010), "Asymmetric Peer Effects in Physician Prescription Behavior: The Role of Opinion Leaders," *Journal of Marketing Research,* forthcoming.

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 (2), 204–211.

Onnela, J.-P., J. Saramaki, J. Hyvonen, G. Szabo, D. Lazer, K. Kashi, J. Kertesz, and A.-L. Barabasi (2007), "Structure and Tie Strength in Mobile Communication Networks," *Proceedings of the National Academy of Sciences*, 104, 7332–7336.

Reinartz, Werner and V. Kumar (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration," *Journal of Marketing*, 67 (1), 77–99.

Reingen, Peter H. and Jerome B. Kernan (1986), "Analysis of Referral Networks in Marketing: Methods and Illustration," *Journal of Marketing Research,* 23 (4), p. 370-378.

Rogers, Everett M. (2003) *Diffusion of Innovations*. New York: The Free Press

Rosen, Emanuel (2009). *The Anatomy of Buzz Revisited: Real-life Lessons in Word of Mouth Marketing*. New York: Broadway Business

Rust, Roland T., Katherine N. Lemon, and Valerie Zeithaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy," *Journal of Marketing*, 68 (1), 109.

———. and Tuck Siong Chung (2006), "Marketing Models of Service and Relationships," *Marketing Science*, 25 (6), p. 560-580.

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 (1), 84–94.

Strang, David and Nancy Brandon Tuma (1993), "Spatial and Temporal Heterogeneity in Diffusion," *American Journal of Sociology*, 99 (3), 614-639.

Tellis, Gerard J. (2004) *Effective advertising: Understanding when, how, and why advertising works.* Sage Publications.

Trope, Yaacov and Nira Liberman (2003), "Temporal Construal," *Psychology Review*, 110 (3), 403–421.

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 (5), p. 90

Van den Bulte, Christophe and Stefan Stremersch (2004), "Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test," *Marketing Science* 23 (4), 530–544.

Van den Bulte, Christophe and Garry L. Lilien (2001), "Medical Innovation Revisited: Social Contagion versus Marketing Effort," *The American Journal of Sociology*, 106 (5), 1409–1435.

Van den Bulte, Christophe 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 (3), 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.

Wuyts, Stefan, Stefan Stremersch, Christophe Van den Bulte, and Philip Hans Franses (2004), "Vertical Marketing Systems for Complex Products: A Triadic Perspective," *Journal of Marketing Research*, 41 (4), 479-487.

Table 1a: Descriptive Statistics for the Discrete Variables in the Model

Variable Name	Unit of Analysis	Proportion in the Dataset
Student	1= Student	4.07%
Ethnic Group 1	1= Ethnic Group Member	8.25%
Ethnic Group 2	1= Ethnic Group Member	9.69%
Ethnic Group 3	1= Ethnic Group Member	12.15%
Gender	1= Female 0=Male	44.65% 55.35%

Table 1b: Descriptive Statistics for the Continuous Variables in the Model

Variable Name	Description	Unit of Analysis	Mean	STDEV
Exposure*	The number of defecting neighbors	#	.52	.90
Average Tie Strength with defecting neighbors**	The sum of tie strengths with defecting neighbors, divided by the number of defecting neighbors	%	7.93	17.03
Average Homophily with defecting neighbors**	The sum of Homophily scores with defecting neighbors, divided by the number of defecting neighbors	%	37.95	19.12
Economic Incentive	The ratio of within-network communication to the total communication	%	41.00	24.33
Avg. Monthly Usage	The average monthly usage of the customer throughout 2008	Hours	10.78	10.93
Time from Enrollment	Customer's tenure with this provider	Years	4.96	3.43

* See complete distribution in Figure 2

** Statistics are calculated for individuals who were exposed to defecting neighbors

Table 2: Exposure to Defectors **

Variable	Unit of Analysis	Model 1: Mere Exposure		Model 2: Basic Exposure Model		Model 3: Exposure Model Including Relationship and Similarity Distance Variables	
		Parameter Estimate	Hazard Ratio	Parameter Estimate	Hazard Ratio	Parameter Estimate	Hazard Ratio
Exposure (1st Degree Defections)	(# of defecting neighbors)	.856 (.005)	2.355	.921 (.006)	2.511	.604 (.013)	1.813
Average Tie strength with defecting neighbors	(%)					.020 (<.001)	1.020
Average Homophily with defecting neighbors	(%)					.011 (<.001)	1.011
Economic Incentive	(%)			-.057 (< .001)	.945	-.056 (<.001)	.945
Avg. Monthly Usage	Hours			.008 (< .001)	1.008	.009 (<.001)	1.009
Time from Enrollment	Years			-.021 (.001)	.980	-.021 (.001)	.979
Student	1 = Student			-.055 (.020)	.947	-.075 (.021)	.928
Ethnic Group 1	1= Ethnic Group Member			-.330 (.020)	.719	-.344 (.020)	.709
Ethnic Group 2	1= Ethnic Group Member			-.386 (.021)	.680	-.365 (.020)	.694
Ethnic Group 3	1= Ethnic Group Member			-.201 (.015)	.818	-.207 (.015)	.813
Gender	1 = Female			-.062 (.009)	.940	-.057 (.009)	.944

	Model 1	Model 2	Model 3
-2 LOG L	1,695,899	1,238,385	1,233,746
AIC	1,695,901	1,238,403	1,233,768
SBC	1,695,910	1,238,482	1,233,865

** All parameter estimates are significant at p<0.01

Table 3: Social Influence Decrease over Time **

Variable	Unit of Analysis	Model 4 Parameter Estimate	Model 4 Hazard Ratio
$Exposure_t$	(# of defecting neighbors at time t)	.875 (0.008)	2.400
$Exposure_{t-1}$	(# of defecting neighbors at time t-1)	.413 (0.017)	1.512
$Exposure_{t-2}$	(# of defecting neighbors at time t-2)	.211 (.020)	1.235
$Exposure_{t-3}$	(# of defecting neighbors at time t-3)	.161 (.021)	1.175
$Exposure_{t-4}$	(# of defecting neighbors at time t-4)	.145 (.021)	1.156
Economic Incentive	(%)	-.042 (<.001)	.959
Avg. Monthly Usage	(hours)	-.004 (<.001)	.996
Time from Enrollment	(years)	-.019 (.002)	.981
Student	1 = Student	-.044 (.026)	.957
Ethnic Group 1	1= Ethnic Group Member	-.330 (.023)	.719
Ethnic Group 2	1= Ethnic Group Member	-.388 (0.024)	.678
Ethnic Group 3	1= Ethnic Group Member	-.175 (.018)	.839
Gender	1 = Female	-.050 (.011)	.951

-2 LOG L	916,482
AIC	916,508
SBC	916,618

** All parameter estimates are significant at p<0.01

Figure 1:

n Neighbor's Previous Defection on Current Defection

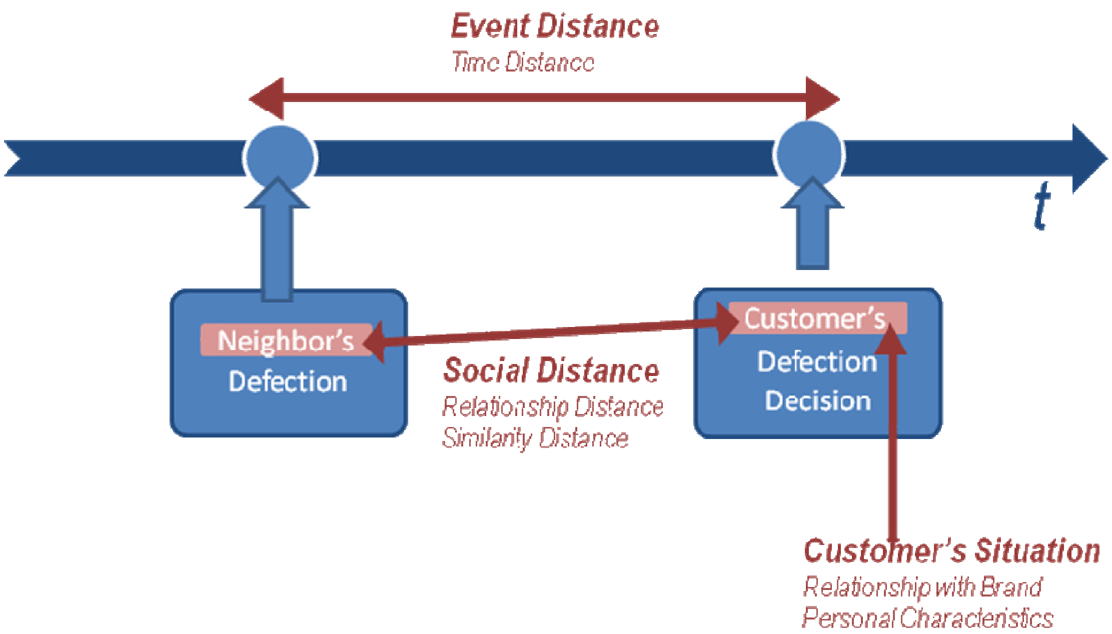

Figure 2

Distribution of Customers' Exposure to Defectors

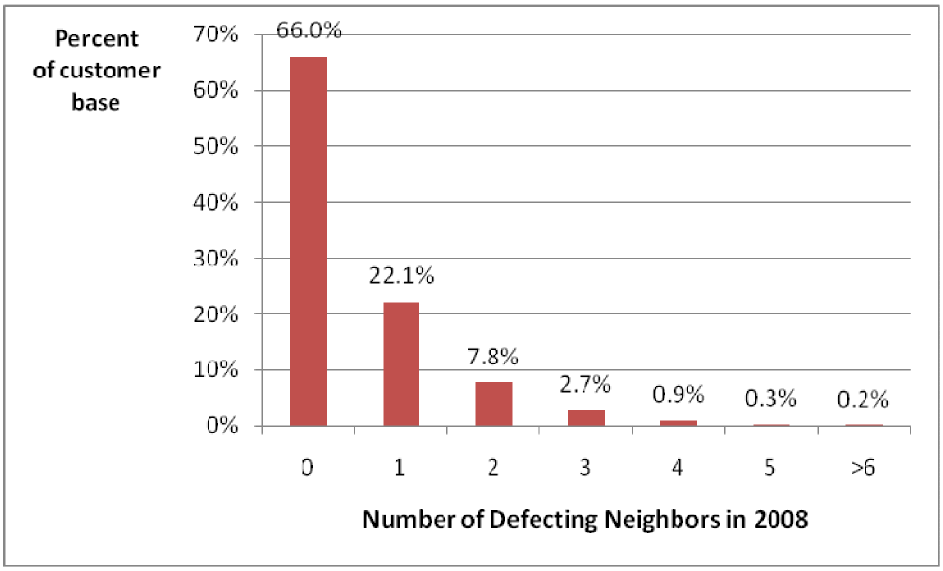

Figure 3
Exposure to Defecting Neighbors - Defecting and Non-Defecting Customers

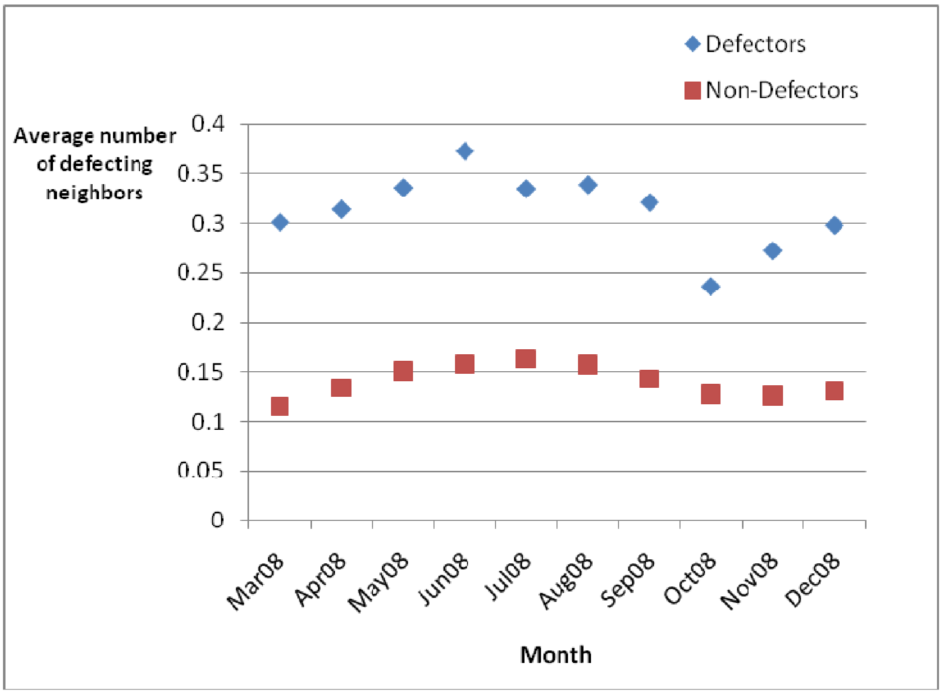

Figure 4a

Average Tie Strength with Defecting Neighbors vs. the Defection Percent

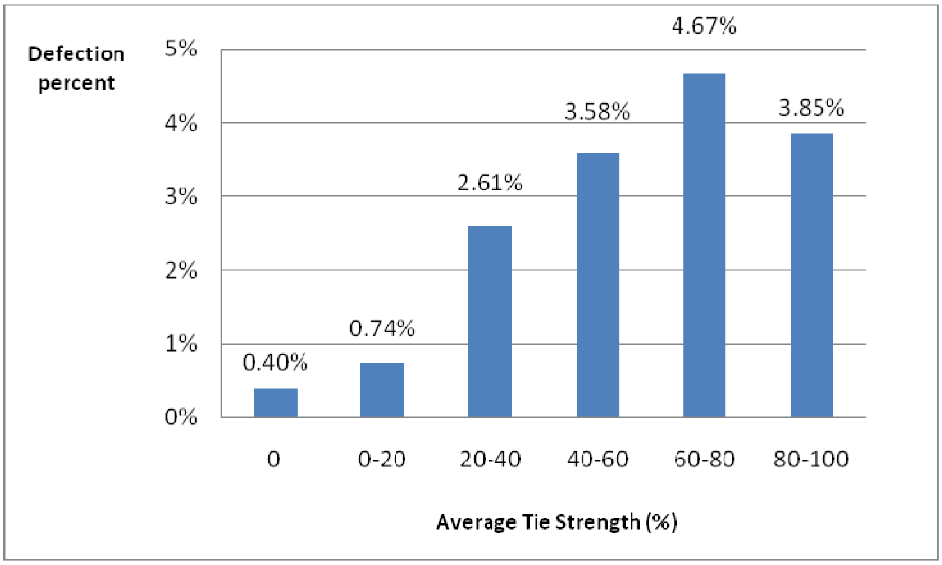

Figure 4b

Average Homophily with Defecting Neighbors vs. the Defection Percent

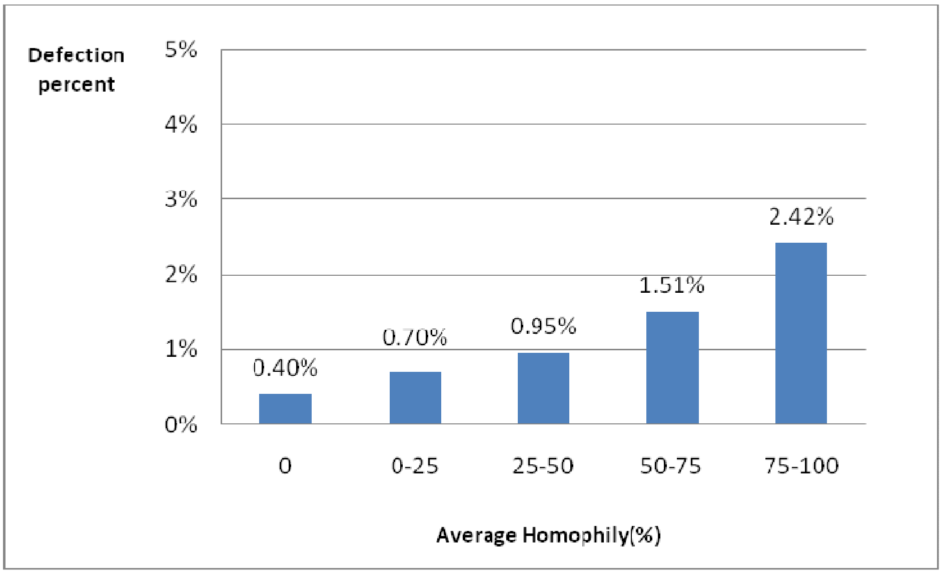

Figure 5

Hazard Ratio as a Function of Time Distance

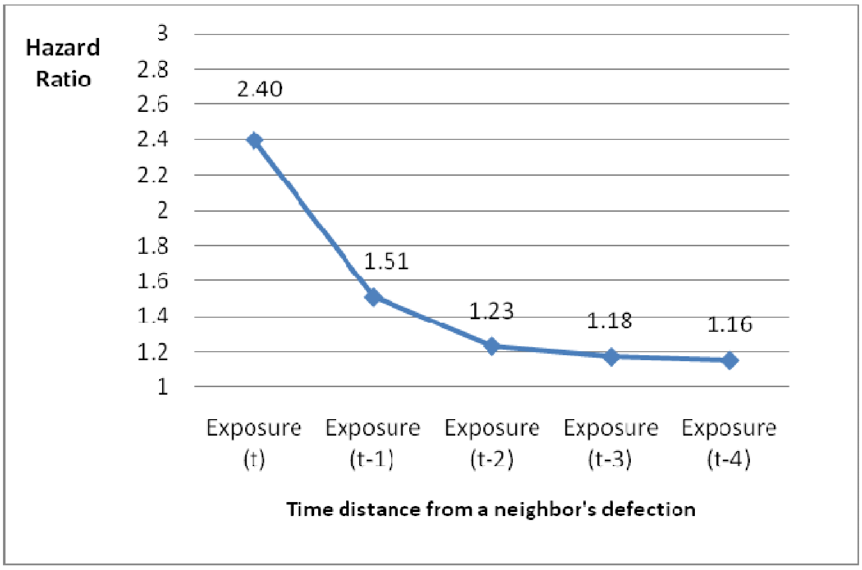

Figure 6a

Hazard Ratio as a Function of Time Distance: Heavy vs. Light Users

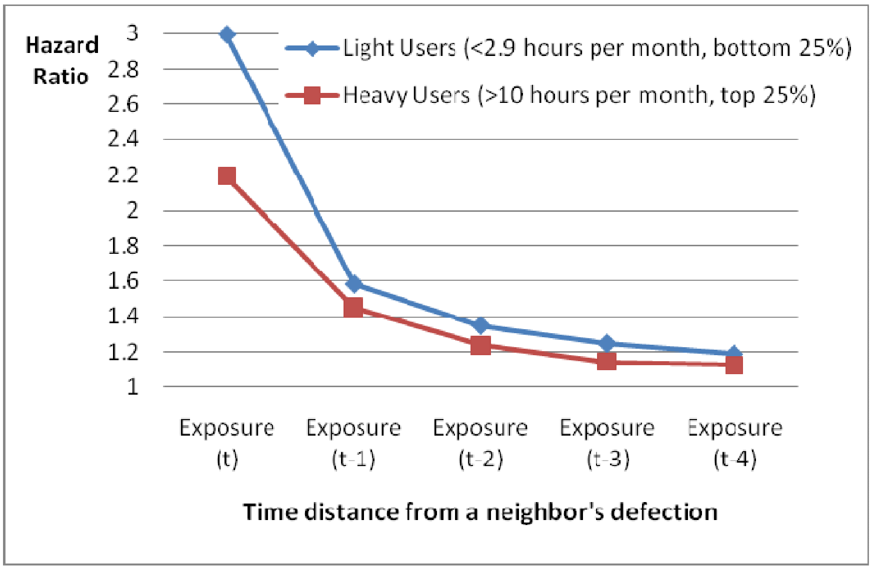

Figure 6b

Hazard Ratio as a function of Time Distance: Tenured vs. New Customers