

THE SOCIAL ASPECTS OF CUSTOMER CHURN

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Report Summary

Customer defection is of much concern to firms and has been the focus of numerous studies, yet in contrast to customer acquisition (new product adoption) its social aspects are largely unexplored. In this study we aim to assess the role of a customer's social network in his or her defection decision. To do so we use a database of more than one million personal customers of a cellular company. Using data on the communication among customers, we were able to create a large-scale social system composed of the individual social networks of those customers. Our data set includes the entire relevant customer base, which helps us to avoid the non-trivial problems associated with sampling from large-scale networks.

We estimate a hazard model that combines social network information with data on customer retention to assess the extent to which customers' defection from a cellular provider might be affected by their exposure to defections of their social neighbors.

Our findings indicate that a customer's social network affects the defection decision significantly; exposure to a defecting neighbor is associated with an increase of up to 150% in one's hazard of defection, and 80% when controlling for a host of social, personal and purchase related variables. Furthermore, we show how strength of ties and the degree of similarity (homophily) to defecting neighbors have a significant effect on this phenomenon, and observe that the social defection effect decays exponentially with the passage of time following a neighbor's defection event. We also demonstrate how customer loyalty moderates the social effect on retention. These results carry important implications for our understanding of the drivers of customer defection, and they should be taken into account by firms that aim to predict and affect the retention of their customers.

1. 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 (Ryan and Gross 1943; Rogers 2003). 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), leaving employment in a firm (Castilla 2005), or ceasing consumption of unhealthy foods (Christakis and Fowler 2007).

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 (Rust and Chung 2006; Villanueva and Hanssens 2007; Bolton 1998; Verhoef 2003). 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 (Onnela et al. 2007; Hill, Provost and Volinsky 2006), 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 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 look at the following three types of 'distance' measures: *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 neighbors defection can increase the hazard of a focal customer's defection by up to 150%; and that even when controlling the characteristics of the defecting customer, its 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. We see that both the relationship distance (tie strength) and the similarity distance (homophily) between an individual and previous defectors in his social network affect this individual's probability of defection in a significant way. Time distance, plays a significant role as well: The effect of defections 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.

2. Retention and Social Effects

2.1 Background

The importance of customer retention stems mainly from its close connection to a firm’s bottom line (Rust and Chung 2006; Gupta and Zeithaml 2006); retention typically serves as a mediator in the satisfaction–profitability link (Villanueva and Hanssens 2007; Rust, Lemon, and Zeithaml 2004). 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 (Gupta et al. 2006, Bolton, Lemon, and Verhoef 2004). 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 (Cooil et al. 2007; Bolton, Lemon and Bramlett 2006; Bolton 1998; Anderson 1998), customer knowledge (Capraro, Bronarczyk and Srivastava 2003), current and expected switching costs (Lemon, Barnett-White and Winer 2002), product assortment (Borle et al. 2005), and various personal characteristics (Cooil et al. 2007). 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 (Muller, Peres and Mahajan 2009; Van den Bulte and Wuyts 2007; Keller and Berry 2003).

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, 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 or through normative and social pressure. Social influence also occurs when, as a result of network externalities, the number of other users provides information on the value of a product (Van den Bulte and Lilien 2001; Muller, Peres and Mahajan 2009).

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): Social distance, Event distance and individual customer situation.

Insert Figure 1 approximately here

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 (Van den Bulte and Wuyts 2007; Godes and Mayzlin 2004). 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 (Ryu and Feick 2007; Wuyts et al. 2004; Brown and Reingen 1987). 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 (Rogers 2003, Brown and Reingen 1987). 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.

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 time dynamics of word of mouth, following an event have scarcely been explored (De Matos and Rossi 2008). One exception is a study by Strang and Tuma (1993), who suggest that the influence of a prior adoption event on further adoptions decays exponentially over time after the event's occurrence.

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 similarity. 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 (Rosen 2009; Rogers 2003; Muller, Peres and Mahajan 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 observes 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.

2.2 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 social network 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 (Wuyts et al 2010; Rosen 2009; Christakis and Fowler 2009). Although the social effects of defection may not be as substantial as in the case of adoption of new products, 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). Furthermore, the mere knowledge of another customer's defection may serve as a signal to the focal customer of a neighbor's revealed preferences; one may expect some normative pressure in this relatively high-involvement service.

In addition, the cellular communication industry is often characterized by a pricing-driven network effect (Birke and Swan 2006, Farrel and Klemperer 2006). In practice, providers

have generated this effect by offering subscribers cheaper rates for calls within a specific provider's network. The extent to which such network externalities have influenced the growth of cellular services remains to be determined (Libai, Muller and Peres 2009), yet this pricing scheme does have the potential to affect defection. If this pricing method is in place, the churn of a member of the social network of a focal customer may reduce the utility of that brand for that customer, and thus can affect his or her defection probability.

Hence, we expect that social effects may play a role in defection. The following propositions follow the framework we present above.

*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.*

4. 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 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.

Consistent with Onnela et al. (2007), we used three months of communication data between the customers to reconstruct each customer's social network within the provider's

network. 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). As seen in Figure 2, 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.

Insert Figure 2 approximately here

5. 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). Specifically, 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 (Rust and Chung 2006; 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 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 (Reinartz and Kumar 2003; Bolton 1998), 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).

5.1 Variables

Exposure. The exposure variable represents the presence of previous defectors in the social system of a defector (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. It is not trivial to conclude what influences a customer's decision to defect following a neighbor's defection. Although the effect may indeed be based on communication, i.e., the customer receives new information from the neighbor regarding his or her defection, a customer may also be affected by loss of economic utility resulting from the neighbor's defection. Indeed, 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).

Note that 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, whenever a family moves to another supplier at the same time, we count it as one defection.

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).

$$EI_i = \frac{\text{Within_Network_}MOU_i}{\text{Total_}MOU_i}$$

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.

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. However, since there had been differential pricing in the past, it is not clear to what extent some customers may still *perceived* a rate difference.

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 provide information about the variables used in this study.

Insert Tables 1a and 1b approximately here

5.2 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 Appendix A we specify how we attempted to mitigate the possible biases.

5. Results

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

Figure 3 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 ($p < 0.001$).

Insert Figure 3 approximately here

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.

Insert Table 2 approximately here

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 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.

Insert Figures 4a and 4b approximately here

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 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 5a). This model's results support proposition 4.

Insert Table 3 approximately here

Insert Figure 5 approximately here

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 less clear. At table 2 it is positive (contrary to expectation) yet relatively to other variables, the effect is very small. At table 3, when looking at the dynamics over time, it is negative. It is thus possible that the usage effect happens more in higher and lower levels, and so 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.

Insert Figures 6a – 6b approximately here

6. 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. Looking only at exposure, we observed that the presence of a previous defector in a focal customer's social network increased the customer's defection probability by 135%. 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 (Strange and Tuma 1993). 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 (Reichheld 1996). 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.

7. Future Research and Limitations

We have mentioned a number of avenues for future research, and more should be acknowledged. In this study 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., quitting smoking) it is suggested that such influence takes place (Christakis and Fowler's 2008); 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.

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Appendix A: 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.

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	#	0.52	0.90
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 **

		Model 1		Model 2		Model 3	
		Mere Exposure		Basic Exposure Model		Exposure Model Including Relationship and Similarity Distance Variables	
Variable	Unit of Analysis	Parameter Estimate	Hazard Ratio	Parameter Estimate	Hazard Ratio	Parameter Estimate	Hazard Ratio
Exposure (1st Degree Defections)	(# of defecting neighbors)	0.856 (0.005)	2.355	0.921 (0.006)	2.511	0.604 (0.013)	1.813
Average Tie strength with defecting neighbors	(%)					0.020 (<0.001)	1.020
Average Homophily with defecting neighbors	(%)					0.011 (<0.001)	1.011
Economic Incentive	(%)			-0.057 (< 0.001)	0.945	-0.056 (<0.001)	0.945
Avg. Monthly Usage	Hours			0.008 (< 0.001)	1.008	0.009 (<0.001)	1.009
Time from Enrollment	Years			-0.021 (0.001)	0.980	-0.021 (0.001)	0.979
Student	1 = Student			-0.055 (0.020)	0.947	-0.075 (0.021)	0.928
Ethnic Group 1	1= Ethnic Group Member			-0.330 (0.020)	0.719	-0.344 (0.020)	0.709
Ethnic Group 2	1= Ethnic Group Member			-0.386 (0.021)	0.680	-0.365 (0.020)	0.694
Ethnic Group 3	1= Ethnic Group Member			-0.201 (0.015)	0.818	-0.207 (0.015)	0.813
Gender	1 = Female			-0.062 (0.009)	0.940	-0.057 (0.009)	0.944
-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	Hazard Ratio
Exposure _t	(# of defecting neighbors at time t)	0.875 (0.008)	2.400
Exposure _{t-1}	(# of defecting neighbors at time t-1)	0.413 (0.017)	1.512
Exposure _{t-2}	(# of defecting neighbors at time t-2)	0.211 (0.020)	1.235
Exposure _{t-3}	(# of defecting neighbors at time t-3)	0.161 (0.021)	1.175
Exposure _{t-4}	(# of defecting neighbors at time t-4)	0.145 (0.021)	1.156
Economic Incentive	(%)	-0.042 (<0.001)	0.959
Avg. Monthly Usage	(hours)	-0.004 (<0.001)	0.996
Time from Enrollment	(years)	-0.019 (0.002)	0.981
Student	1 = Student	-0.044 (0.026)	0.957
Ethnic Group 1	1= Ethnic Group Member	-0.330 (0.023)	0.719
Ethnic Group 2	1= Ethnic Group Member	-0.388 (0.024)	0.678
Ethnic Group 3	1= Ethnic Group Member	-0.175 (0.018)	0.839
Gender	1 = Female	-0.050 (0.011)	0.951

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

** All parameter estimates are significant at p<0.01

Figure 1:
The Effect of a Neighbor's Previous Defection on Current Defection

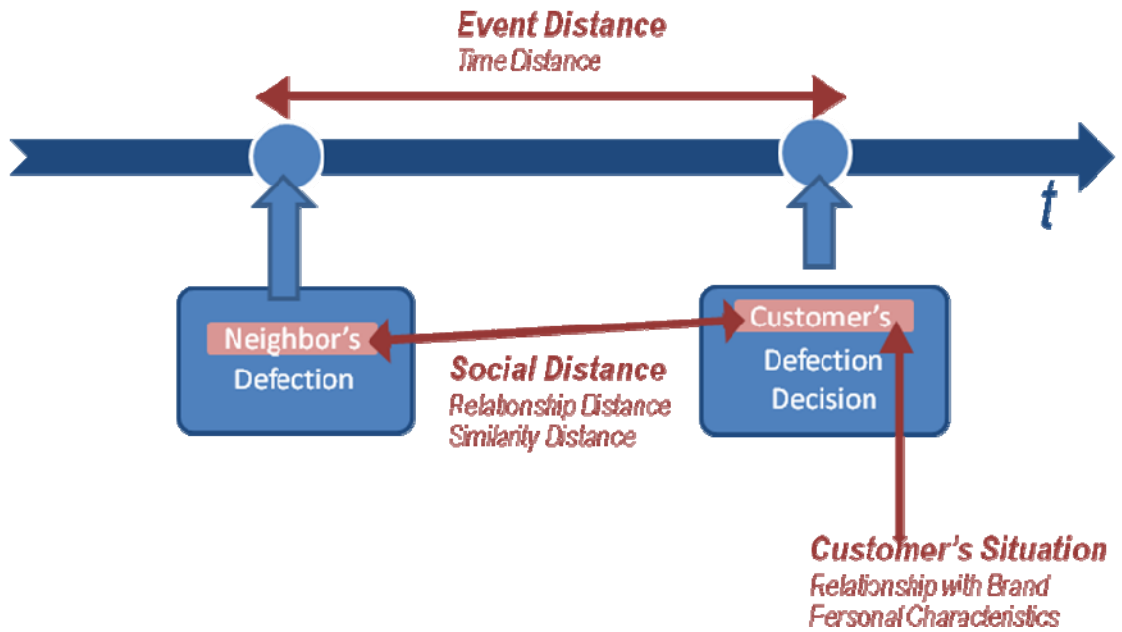


Figure 2
Distribution of Customers' Exposure to Defectors

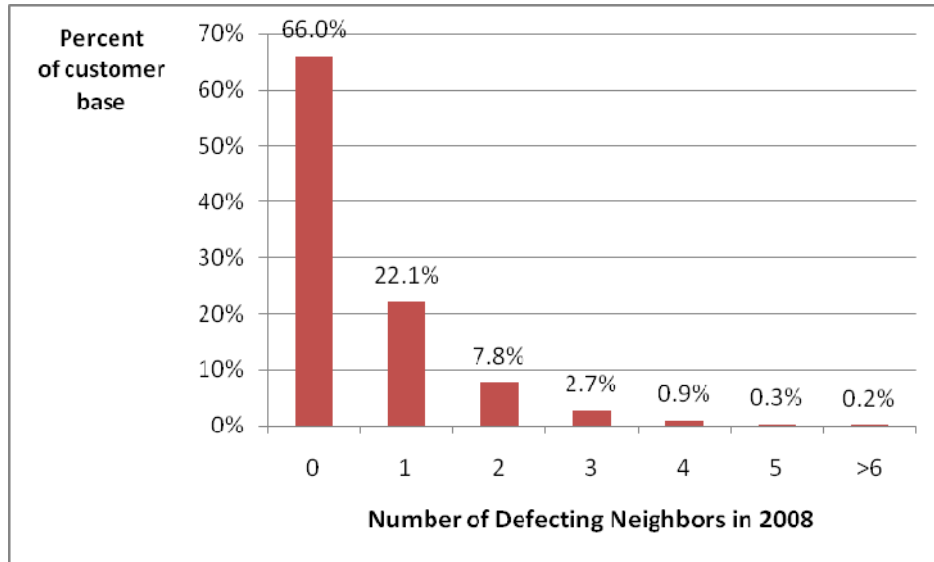


Figure 3
Exposure to Defecting Neighbors - Defecting and Non-Defecting Customers

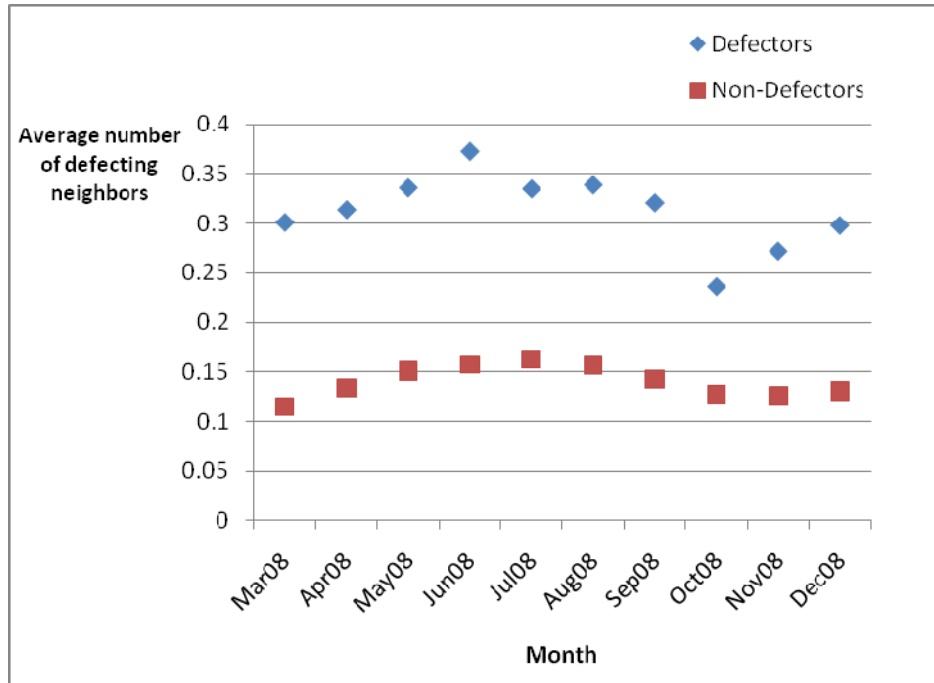


Figure 4a
Average Tie Strength with Defecting Neighbors vs. the Defection Percent

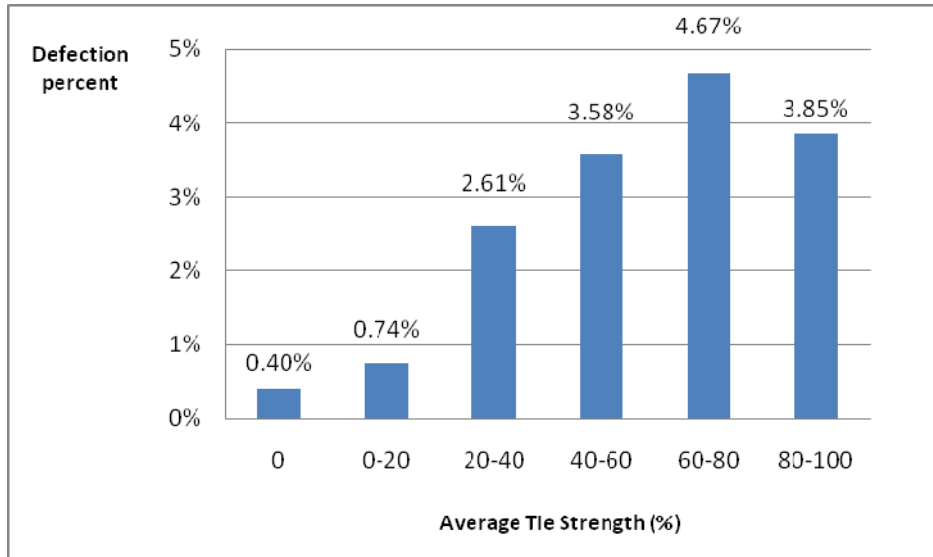


Figure 4b
Average Homophily with Defecting Neighbors vs. the Defection Percent

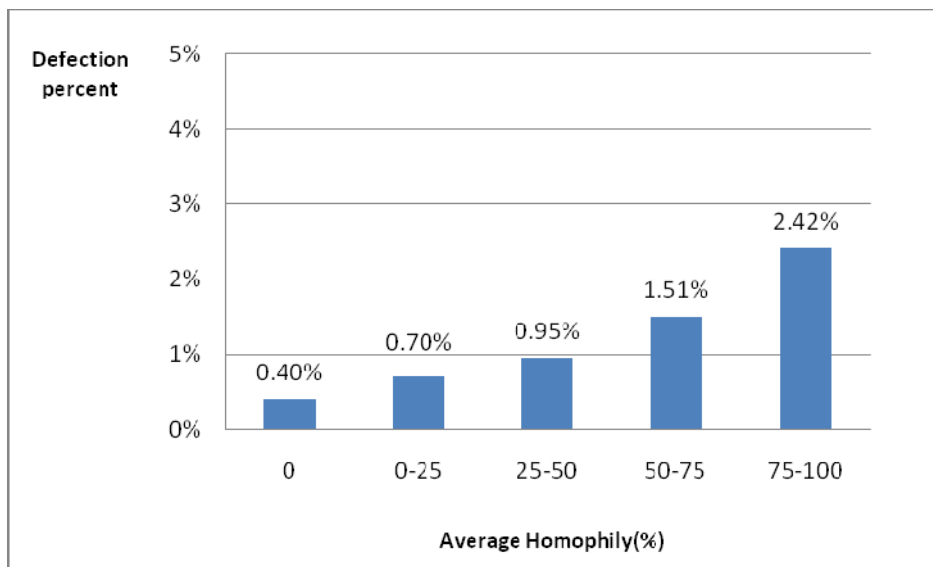


Figure 5
Hazard Ratio as a Function of Time Distance

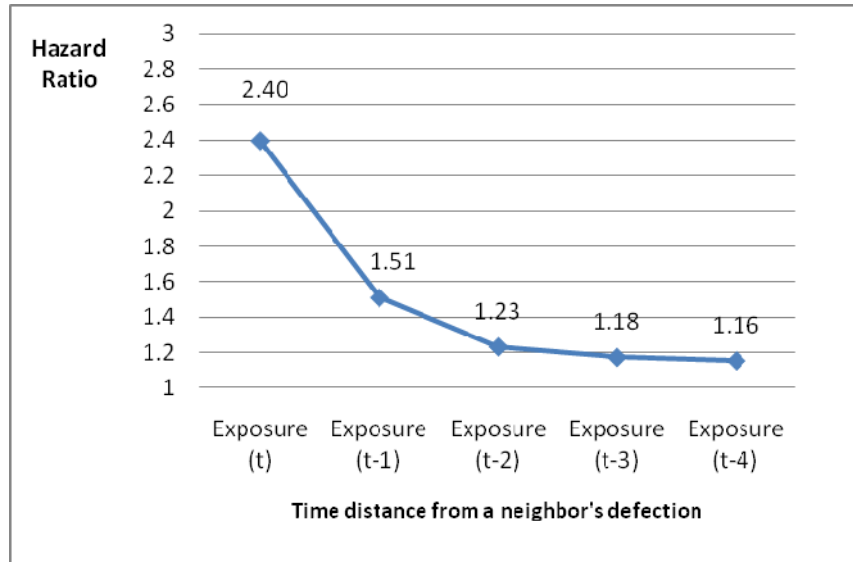


Figure 6a

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

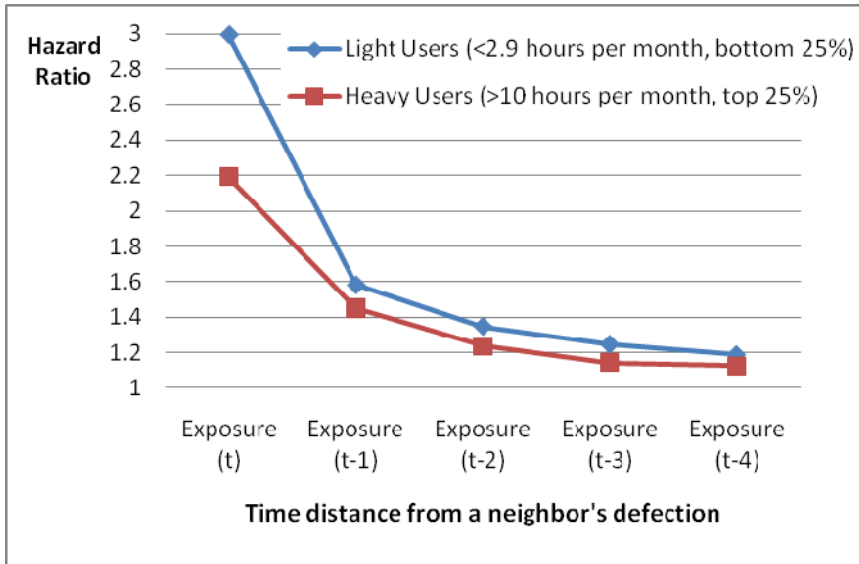


Figure 6b

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

