Determinants of Subscriber Churn in Wireless Networks: The Role of Peer Influence*

[Extended Abstract]

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ABSTRACT
Subscriber churn is a top challenge for wireless carriers. Understanding the determinants of churn is key for carriers to identify potential churners and apply effective retention strategies to reduce subscriber loss. In this paper, we apply generalized propensity score matching to separate peer influence from other confounding factors that might affect churn. Our empirical analysis, developed over a large scale wireless network, confirms that peer influence plays a role in churn. The estimated marginal influence of having a first friend churn is roughly 3%. While the marginal effect of friends' churn decreases significantly as more friends do so, contagious churn is still a significant part of the story beyond high churn rates in the mobile industry.

1. INTRODUCTION
In today's competitive wireless industry, subscriber churn is considered to be the "biggest issue for all wireless carriers" [7]. Preserving the existing subscriber base is of crucial importance for carriers to ensure their profitability. Understanding determinants of churn becomes fundamental for carriers so that they can identify potential churners and apply appropriate retention strategies to reduce subscriber loss. However, the complex nature of churn poses significant challenges to carriers that pursue effective churn management solutions to deal with all kinds of churn problems. As a consequence, most carriers focus only on retaining their most valuable subscribers.

Advances in studying the effect of social influence on subscriber churn in wireless networks have received much attention in recent times. [5] found that the likelihood of churn increases with the number of friends who have already churned. [6] also confirmed that the "word-of-mouth" effect has a positive impact on subscriber's churn. However, work that identifies contagious churn on a causal sense and separates it from confounding effects such as homophily still lacks. Correlation in the behavior among people who share social ties can be explained by both peer influence and their inherent similarities [10]. Therefore, misattribution of homophily to contagion, or-and vice versa, needs to be carefully thought from an empirical point of view.

Numerous studies on identification of peer influence in other networked context have been proposed (e.g. [1, 4, 13]). [2] used dynamic propensity score matching (PSM) to estimate the effect of contagion in the adoption of an online service by analyzing a community of instant messenging users. Their findings suggest that homophily accounted for much of the adoption previously perceived as peer influence. However, [2] dichotomize the treatment due to the binary nature of treatment regime. The applicability of PSM therefore is confined, as effects of different numbers of adopter friends are overlapped. To overcome this problem, in this paper, we apply a generalized propensity score matching (GPSM) method to separate peer influence from homophily. We perform our empirical analysis on a massive dataset from a major European wireless carrier (hereafter refer to as EURMO). We have call detail records (CDR) and tariff plan information from EURMO. The GPSM method allows us to estimate the magnitude of the contagion effect given different numbers of friends who churn. This can provide us with more information on the marginal effect of peer influence and thus help us better understand the role of peer influence on churn.

2. DATA
The EURMO dataset includes CDRs for roughly 4 million prepaid subscribers between August 2008 and June 2009. For each call we know the caller and the callee, the duration and time of the call. For each SMS we know the sender and receiver and the time of the SMS. Subscribers are identified by their anonymized phone number. For each subscriber, we know their tariff plan at all times. Understanding subscriber churn for prepaid consumers is quite different from postpaid subscribers. First, we have little demographic information on prepaid subscribers. Second, the usage pattern of prepaid subscribers is more irregular than that of postpaid subscribers. Third, prepaid subscribers churn by ceasing usage whereas postpaid subscribers explicitly inform the carrier when they want to do so. After consulting with the carrier, we use its definition of churn and thus assume that a prepaid subscriber churns if she does not place a call or sends a SMS for three consecutive months.

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Variable	Description	MD_C	SD_C	MD_NC	SD_NC
Time Invariant Individual					
PLAN_ID	The ID for the tariff plan	1.09	1.15	1.35	1.95
Time Variant Individual					
#CALL	Number of calls made or received per day	0.24	2.29	1.41	3.16
AIRTIME	Duration of calls made or received (in min)	0.22	4.68	1.59	7.32
#NEIGHBOR	Number of friends	10	46.37	64	104.40
#SMS	Number of SMS sent or received	0.012	4.51	0.30	20.14
LIFETIME	Duration since subscription to carrier (in month)	3.67	12.08	15.37	18.58
RCO	Ratio of calls to other networks	0.2	0.31	0.15	0.23

Table 1: List of covariates extracted from EURMO, MD is median and SD is standard deviation, C stands for churner and NC stands for non-churner

We use a random sample of 10,000 subscribers together with their 690,000 friends (430,000 in the same network). Two subscribers are called friends if at least they exchange one call in the same calendar month. We observe network dynamics: every month new subscribers join EURMO, existing subscribers leave EURMO and subscribers call and/or text different friends. Therefore, we aggregate time-varying individual subscriber usage and time-invariant characteristics at the monthly level (Table 1). Over the eleven months in our period of analysis, the 10,000 subscribers in our sample placed 6.5 million calls. 2,282 of them left EURMO, which amounts to an average monthly churn rate of 2.07%.

We find that the subscribers that churn have much less usage and fewer friends than the subscribers who do not both in terms of number of calls and airtime. Moreover, we also observe that both subscribers who churn and do not have much more usage within the network. This is sensible because calls across carriers cost more as carriers pass on to subscribers part of the interconnection charges. We also find that the conditional churn probability decreases with the subscriber's lifetime with the carrier. One possible explanation can be that subscribers become loyalty to carriers over time. We also note that subscribers exhibit a significantly higher churning rate during the first three months they sign up with the carrier. This implies that carriers should pay particularly attention to these subscribers who just join the network and thus build up good customer relationships with them to keep them in the firm, as they become more valuable with time.

3. METHODOLOGY

Propensity Score Matching (PSM) is a widely used method to evaluate the causal treatment effect from observational data in various empirical research fields [11], in particular when the assignment of a binary treatment is not random and counterfactual outcomes are unavailable. With PSM units from a treated group are matched to those in a control group using a propensity score. Differences in the behavior of these pairs of units measure the effect of the treatment. [8] extended and proposed this framework to allow for continuous levels of treatment. Formally, consider a set of N subscribers and let i denote a single subscriber. Let $P = \{1, \dots p\}$ represent a set of time periods. We observe a vector of pre-treatment covariates X_{ip} as shown in Table 1 at each time period. We define the treatment at each period for each subscriber as her exposure to a certain number of friends who churned in the last time period τ_{ip-1}. Very few subscribers in our sample have more than 3 friends who churn. Therefore, we decided to use four levels of treatment: $T \in \{0, 1, 2, 3\}$, to indicate whether 0, 1, 2 or 3 or more friends churn, respectively. The outcome of interest is whether subscriber i churns in time period p: $Y_{ip} \in \{0, 1\}$.

GPSM requires weak unconfoundedness: $Y(t) \perp\!\!\!\perp T|X$. In our case, though the number of friends who churn at time $p-1$ is not randomly assigned, we observed all variables that can affect both the subscriber's churn at time p and the likelihood of receiving treatment (justification of this assumption is discussed in the next section). We estimate the conditional distribution of the number of friends who churn given these covariates to estimate the generalized propensity score (GPS) for each subscriber, R_i (we assume that the logarithm of the number of friends who churn is normally distributed). We also investigate the balancing property for our covariates adjusted by GPS by testing whether the mean of one of the four treatment levels was different from the mean of the other three treatment levels. We generally observe moderate evidence against the balancing properties according to a two-sided t-test.

We denote the dose response function as a set of potential outcomes given the treatment level t: $\{Y_{ip}(t)_{t \in T}\}$ where T is the set of potential treatment values. Then the conditional expectation of churn is a function of number of friends who churn T and of the GPS R:

$$\beta(t, r) = E[Y_{ip}(t)|r(t, X_{ip}) = r] = E[Y_i|T_{ip-1} = t, R_i = r]$$

We use a polynomial approximation of order two to regress the subscribers' churn Y_i on the number of churned friends T_i, and the GPS R_i.

$$Y_i = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 T_i R_i$$

Therefore, the effect of peer influence on churn is the average conditional expectation over GPS at a particular number of friends who churn:

$$\mu(t) = E[\beta(t, r(t, X_i))]$$

Taking derivatives, we can easily obtain the marginal effect associated with one more friend churn on the subscriber's churn for different levels of treatment.

4. RESULTS AND DISCUSSIONS

For each month we evaluate the dose response function separately (we use the Stata package provided by [3]). We use

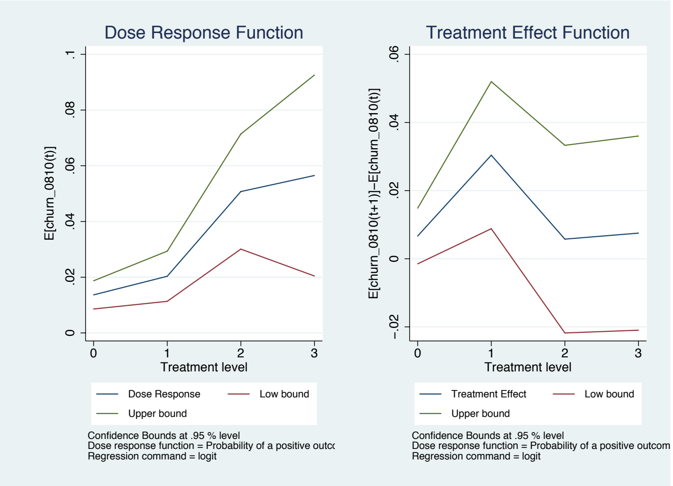

Figure 1: Dose response function and treatment effect function in October 2008

bootstrapping to calculate the asymptotic standard errors and confidence intervals. Figure 1 shows the average dose response and treatment effect for October 2008 (estimates for other months exhibit similar characteristics). The figure on the left shows that the effect on subscribers churn increases with the number of friends who churn. For example, the probability of churn for subscribers who have two friends who churned in September 2008 is 4% higher than that for subscribers who had no friends who churned in September 2008. The figure on the right shows that the marginal influence (the effect of having one more friend who churns) decreases as more friends churn. For example, having one friend who churns compared to having no friends who do so will lead to an increase of 3% in the probability of churn but having two or more friends who churn compared to having one friend who churns will increase the probably of churn by only 1%. Our results confirm the positive effect of peer influence on churn. When we remove the selection bias due to the homophily, we still observe contagious churn.

We notice the argument made by [12] that the plausibility of the unconfoundedness assumption remains unidentifiable from observational data. As long as there are systematic differences in unobserved covariates, we cannot safely conclude that the unconfoundedness assumption holds. Therefore, we acknolwedge that our results may still be biased. As future work, we will perform sensitivity analysis to check the robustness of our results. One possible way to do so is to relax the unconfoundedness assumption, introduce an artificial unobserved variable and reestimate the dose response function to check whether the presence of unobserved heterogeneity may significantly change our results [9].

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