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A Dyad Model of Calling Behaviour with Tie Strength Dynamics

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Abstract

This paper investigates the dynamic relation between callers' social ties and their wireless phone service consumption. We construct a large pair-level panel dataset with information on the number of each pair's common contacts, calling activities, prices, and each caller's characteristics over a one-year time period. We estimate a dynamic model that encapsulates the evolving relationship between each pair of consumers. We find the amount of communications between a pair of consumers increases with the strength of their tie, which is higher when these two consumers share more common contacts. Our results support the reciprocity rule in telephone calls, i.e. when individual A initiates more (less) phone calls to individual B in one month, their social tie will be strengthened (weakened) and individual B will make more (less) calls to individual A in the subsequent months. We demonstrate the implications of our results in evaluating the return of temporary price promotions and designing price plans. Our results underscore the importance of incorporating social network characteristics in the study of telecommunications markets.

Keywords: Social Network, Tie-strength, Reciprocity, Wireless Phone Service

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1. Introduction

This paper investigates how consumers' social network characteristics affect their telecommunications service usage. Communication is social behaviour and telecommunications services must be jointly consumed by multiple people – in other words, "it takes two to tango". This concept of consumption externality has been studied extensively; however, the literature has focused on how the network size (i.e. the number of adopters) interacts with the firms' product and pricing decisions (Shy 2001). Very little attention has been paid to the nature of consumption externality. In the telecommunications market, the volumes of calls are determined not only by the initiating but also by the receiving callers. If a receiving caller expects little value from communicating with the initiating caller, the receiver can control the call volumes by either declining or terminating the calls. Thus, one cannot properly understand the consumers' calling behaviour without knowing who the consumers called and their relationship. To the best of our knowledge, this social aspect of communication behaviour has been absent in the existing empirical literature which focuses on either how consumers decide service usage in response to the nonlinear price plans (Lambrecht and Skiera 2006; Lambrecht, Seim, and Skiera 2007; Iyengar, Jedidi, and Kohli 2008; Huang 2008) or how consumers make service plan choices and usage decisions when they face uncertainty about future usage and/or service quality (Miravete 2003; Narayanan, Chintagunta and Miravete 2007; Iyengar, Ansari, and Gupta 2007).

Understanding the social aspect of communication behaviour is important in designing proper marketing and promotion policies for the telecommunications market. Imagine that a firm needs to evaluate the effect of a temporary price promotion. When the price promotion applies to a grocery product such as laundry detergent in a particular geographic area, the promotion is expected to increase the target households' detergent purchases, and possibly also consumptions. Usually this promotion would not affect the detergent purchases of their friends and acquaintances, nor would it affect the targeted households' perceived values for other grocery products. However, when the price promotion applies to the wireless service, the effect can be extended to the target households' network of social contacts. Since the consumers typically pay for both the incoming and outgoing calls, the firm benefits from the increased communications from not only the initiating households, but also all the receivers not covered by the promotion. In addition, as the target households call their network of contacts more, their social ties would be strengthened and more future communications would be expected. Clearly, a firm would underestimate the benefit of a temporary price promotion if the evaluation is limited only to the target households' consumption changes. Understanding the social aspect of communication behaviour is also critical in designing social network-based price plans such as "friends-and-family plans" (Shi 2003), and in evaluating certain regulatory policies such as the "receiver-pays principle" (Jeon, Laffont, and Tirole 2004).

We take advantage of a unique wireless communications panel dataset with detailed information on calling activities. The dataset is unique because we observe who called whom at what time, how long each phone call lasted, the initiating callers' outgoing call prices, the receiving callers' incoming call prices, and the characteristics of all callers. We develop and estimate a model where each pair of consumers collectively decides on both the number of calls and the duration of calls in each time period. Following the tradition in social network literature, we consider the strength of a pair's social tie to be directional, dynamic, and reciprocal. We postulate and empirically validate that phone calls could enhance the strengths of social ties and that stronger social ties would induce more subsequent phone exchanges. Consumers made more phone calls and spent most of their call volumes among those with which they had strong ties. Our results show that the number of common social contacts shared by a pair of consumers could be a good predictor for the strength of their tie. Our results also validate the reciprocity effect, i.e. caller A's tie strength with B would increase with the number of calls A had received from B in the last period. Finally, we find that the outgoing prices mattered much more than the incoming prices on the number of calls.

Based on our estimation results, we conduct a number of simulations to illustrate the marketing implications of our results. First, we show the extent of biases if one evaluates the effect of a temporary price promotion based on the revenue from only the outgoing or incoming calls but not both. Second, we show how one may underestimate the long-term benefit of a temporary price promotion without incorporating the reciprocity effect. Third, we show the implications of our results to discriminatory pricing. We find that it can be optimal to give consumers free incoming calls (no receiver-pay) if the receiving consumers' incoming prices play a very important role in determining the calling activities.

This paper contributes to the emerging literature on applying social network concepts to marketing. Iacobucci (1996) and more recently Van den Bulte and Wuyts (2007) review the important relation between social networks and marketing. Recent research in marketing has examined other issues such as new product diffusion, commercial World Wide Web structure, and social commerce from a social network perspective (Van den Bulte and Joshi 2007; Katona and Sarvary 2008; Stephen and Toubia 2009). To the best of our knowledge, this is the first empirical study to focus on social network level consumer usage behaviour and offer marketing implications.

The rest of the paper is organized as follows. We lay out the model in Section 2 and describe the data and empirical analysis strategy in Section 3. We report the estimation results and some robustness checks in Section 4. We present some marketing implications in Section 5. Finally, we conclude with main results and implications for future research in Section 6.

2. Model

In this section we develop a dyad model of calling behaviour with dynamic tie strength. We first explain how we measure a pair of consumers' tie strength and how the tie strength evolves over time. We then formulate how a pair of consumers' calling behaviour, both the number of calls and number of calling minutes, depends on their tie strength and other characteristics.

2.1 Tie Strength and the Dynamics

In Granovetter's seminal work (1973), tie strength was defined as a "combination of the amount of time, the emotional intensity, the intimacy (mutual confiding) and reciprocal services which characterize the tie". We view the tie strength between a pair of consumers as a state variable that indexes the closeness and intensity of these two consumers' social relation in all dimensions. Although a social tie can be multi-dimensional, in this paper we use a single-dimensional composite measure that acts as a surrogate for a pair's social relation. Our formulation of tie strength has four properties: *directional, reciprocal, asymmetric*, and *dynamic*. To model these properties, consider a pair of individuals denoted by *i* and *j*. We use $s_{ij,t}$ to represent the strength of tie to individual *i* (with *j*), and $s_{ji,t}$ to represent the tie strength to individual *j* (with *i*) at time *t*. Thus, the tie strengths are directional. The tie strengths are asymmetric because we allow $s_{ij,t}$ to be different from $s_{ji,t}$. We capture the reciprocal and dynamic properties by proposing that the tie strength evolves over time and the current strength of the tie depends on the past interactions. Specifically, we model these properties of the tie strength by assuming the following equation for $s_{ij,t}$:

$$s_{ij,t} = c_1 n_{ij,t-1} + c_2 q_{ji,t-1} + r_1 s_{ij,t-1} \tag{1}$$

where $n_{ij,t-1}$ is the number of common contacts shared by individuals *i* and *j* at time *t-1*, $q_{ji,t-1}$ is the number of calls from *j* to *i* in time period *t-1*, and $s_{ij,t-1}$ is the lagged tie strength in time period *t-1*. Equation (1) captures several important properties of a social tie. First, we use the number of common contacts in two individuals' personal networks as a predictor for their tie strength and expect a positive sign for c_1. The number of common contacts measures the extent of overlapping between social circles, which has been used as a predictor for social closeness (e.g. Alba and Kadushin 1976). In a more recent study on the dynamics of email communications within a major university, Kossinets and Watts (2006) find that people were more likely to interact when they shared acquaintances. Using the number of common contacts as a predictor is also consistent with social networks' transitivity property, which proposes that a tie between individuals A and B and a tie between individuals B and C can often lead to a tie between individuals A and C (Wasserman and Faust 1994). In other words, since individuals A and C share the common contact with individual B, we expect a likely enhancement in the tie strength between A and C. Clearly, when individuals A and C share multiple common ties, we would expect an even stronger enhancement in their tie strength because the transitivity is multiplied.

Second, equation (1) implies a reciprocal effect with a positive c_2. The reciprocal nature has been widely documented in the studies of social exchanges both in personal and business settings (e.g. Blau 1965; Macaulay 1963; Granovetter 1973 and 1985). Montgomery (1996) formalizes the idea of reciprocity in Blau (1965)'s social exchange theory through a repeated game and demonstrates the importance of reciprocal effect in trust-building equilibrium. In this study we hypothesize that a person, by initiating phone calls to another, creates goodwill and strengthens the tie strength to the receiver. More specifically, all else equal, a larger $q_{ji,t-1}$ (more phone calls from individual *j* to individual *i* in the previous period) would lead to a greater $s_{ij,t}$, in other words, a stronger tie to individual *i* with j. As shown later, this results in a reciprocity effect because individual *i* will make more calls to *j* in this time period due to a stronger tie. Finally, the strength of tie is expected to persist over time (e.g., Wellman, Wong, Tindall, and Nazer 1997; Blumstein and Kollock 1988) and thus we expect $r_1>0$.

The tie strength construct and its role in our calling behaviour model share some similarities with the brand loyalty construct and its role in brand choice models (e.g., Guadagni and Little 1983). Both constructs are initiated with past purchase behaviour. However, unlike the brand loyalty measure which depends solely on the past brand choices, the tie strength also depends on network characteristics, specifically, the number of common contacts shared by two people. Second, while brand loyalty goes only one-way from consumers to brands, social tie is a two-way measure that allows for asymmetric strength in two directions. Third, the strength of social tie is more interactive. Specifically, each side takes stocks of other side's calling initiatives and reciprocates in the subsequent periods.

Next we propose a cooperative game framework to derive consumers' calling behaviour as utility-maximizing outcomes.

2.2. Number of Calls and Calling Time: A Cooperative Game Framework

We characterize the communication behaviour between a pair of individuals with two variables: the number of calls and the total calling time. We let $q_{ij,t}$ denote the number of calls and $m_{ij,t}$ denote the total amount of calling time that individual *i* made to individual *j* in period *t.* (In estimation we rescale $m_{ij,t}$ to the logarithm of the total calling seconds from *i* to *j* in period *t*). We follow a cooperative game framework to derive the equilibrium calling behaviour. We adopt the quasi-linear utility framework in Shi (2003) and assume the following quadratic function for the value that individual *i* obtains from initiating $q_{ij,t}$ number of calls to individual *j*.

$$v_i(q_{ij,t}) = (\alpha_1 s_{ij,t} + \alpha_2 X_i)\ q_{ij,t} - \alpha_3 q_{ij,t}^2 - p_{i,t}^{out}\ q_{ij,t} \tag{2}$$

where X_i represents individual *i*'s vector of characteristics and $p_{i,t}^{out}$ is the unit price individual *i* pays for outgoing calls. We then assume individual *j*'s value from receiving $q_{ij,t}$ number of calls from *i* as follows:

$$v_j(q_{ij,t}) = \beta_1 X_j\ \ q_{ij,t} - \beta_2 q_{ij,t}^2 - p_{j,t}^{in}\ q_{ij,t} \tag{3}$$

where X_j represents individual *j*'s vector of characteristics and $p_{j,t}^{in}$ is the unit variable price individual *j* pays for the incoming calls. We expect all the parameters in equations (2) and (3) to be positive. Equation (2) indicates that an individual's value of initiating calls increases with the strength of the individual's tie with the receiver. The value of initiating and receiving calls also depends on the callers' characteristics. The decreasing marginal utility implied by the quadratic function is due to the opportunity cost of time spent in communications.

We assume that the equilibrium communication amount $q_{ij,t}$ is determined by two individuals in a cooperative fashion.[1] Specifically, we follow the cooperative game framework and determine the equilibrium amount of $q_{ij,t}$ by maximizing $\lambda\, v_i(q_{ij,t})$ + (1-λ) $v_j(q_{ij,t})$ where 0≥λ≥1 models the power of individual *i* in the dyad negotiation. Taking the first-order condition with respect to $q_{ij,t}$, we can obtain

$$q^*_{ij,t} = \frac{\lambda\alpha_1}{\omega} s_{ij,t} - \frac{\lambda}{\omega} p^{out}_{i,t} - \frac{(1-\lambda)}{\omega} p^{in}_{j,t} + \frac{\lambda\alpha_2}{\omega} X_i + \frac{(1-\lambda)\beta_1}{\omega} X_j \tag{4}$$

where $\omega = 2\,[\lambda\,\alpha_3 + (1-\lambda)\,\beta_2]$. Adding an intercept ($a_0$) and an error term ($e_{1,ijt}$) to the above first order condition, and simplifying the coefficients through transformation, we obtain the econometric specification for the number of calls.

$$q_{ij,t} = a_0 + a_1 s_{ij,t} + a_2 p^{out}_{i,t} + a_3 p^{in}_{j,t} + a_{X_i} X_i + a_{X_j} X_j + e_{1,ijt} \tag{5}$$

Note that the relative sizes of coefficients a_2 and a_3 in equation (5) reflect the sender and the receiver's power in determining the optimal communication amount.

Next, replacing $q_{ij,t}$ with $m_{ij,t}$, we can derive the econometric specification for the number of calling numbers from a same cooperative game framework.

$$m_{ij,t} = b_0 + b_1 s_{ij,t} + b_2 p^{out}_{i,t} + b_3 p^{in}_{j,t} + b_{X_i} X_i + b_{X_j} X_j + e_{2,ijt} \tag{6}$$

Equations (5) and (6) postulate that, first, the amount of communications increases with the strength of social tie ($s_{ij,t}$). The communications initiated by consumer *i* to *j* should increase with the strength of tie to consumer *i* with *j*. A stronger tie typically indicates a higher value for

[1] Jeon, Laffont, and Tirole (2004) adopt a non-cooperative framework where both individuals behave purely in self interests. In their model each individual chooses an amount that maximizes own value function; that is, *i* and *j* each decides $q_{ij,t}$ to maximize $v_i(q_{ij,t})$ and $v_j(q_{ij,t})$ respectively. The equilibrium $q_{ij,t}$ will be the minimum of the two callers' optimal volumes.

the communications. From equation (1), if i received more phone calls from j in the last period, the strength of tie with j will be strengthened to i in this period. This in turn will increase i's call to j in this time period, and then the strength of tie to j in the next period would be enhanced, so j will make more calls to i in the next period and so on. Mathematically, a larger $q_{ji,t-1} \rightarrow$ a stronger $s_{ij,t} \rightarrow$ a larger $q_{ij,t} \rightarrow$ a stronger $s_{ji,t+1} \rightarrow$ a larger $q_{ji,t+1} \rightarrow \ldots$ This is how the reciprocity effect of calling arrives through the dynamic properties of tie strength.

Equations (5) and (6) also indicate that the amount of communications depends on both the sender's outgoing calling price ($p_{i,t}^{out}$) and the receiver's incoming calling price ($p_{j,t}^{in}$). While the (expected) negative effect of i's outgoing price on the amount of communications is standard, the effect of receiver j's incoming price on the calling amount is unique to two-sided communication services. The receiver is more likely to disconnect the phone or terminate the call sooner when the incoming price is higher. Finally, the amount of communications depends on the callers' characteristics variables such as age and gender.

In summary, we construct a cooperative model to derive the number and duration of calls as the optimal outcome that maximizes the callers' collective values of communications. Because of this, the parameters we estimate in this paper can be considered as transformed micro-parameters and we can conduct counterfactual experiments to examine the marketing implications from our model. Our model is consistent with the sociology literature that views the number and duration of calls as indicators for the callers' tie strength, and aspects of relationships that are related to tie strength as predictors (e.g., Marsden and Campbell 1984).

Finally, we apply the following mean-variance structure to the error terms:

$$\binom{e_{1,ijt}}{e_{2,ijt}} \sim N(\binom{0}{0}, \begin{pmatrix} {\sigma_1}^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & {\sigma_2}^2 \end{pmatrix}) \tag{7}$$

3. Data and Empirical Strategy

Our data was collected from a large Chinese metropolitan market, where we collaborated with a major wireless service operator in the city. The original data from the firm consisted of approximately 38,000 VIP customers – the entire membership list of the firm's VIP club. The VIP club was essentially a loyalty program that provided status rewards such as the privilege to use the airport lounge services. From this original customer-level data, we examined all the individual level calling records and identified 4,342 distinctive pairs of customers. Specifically, we select the pairs to ensure that each person in a pair has made at least one outgoing call to the other person, and the communication history between the pair is at least 8 months long. That is, the time between the first communication and the last communication is at least 240 days long. The selection criteria exclude the pairs with unrealized ties – pairs whose communications could have occurred but did not. We discuss this limitation and potential selection bias further in the Conclusion section.

For the pairs identified, we aggregate the original data to form composite data on the monthly level. Since all the callers were located in the same city, our analysis will focus on local calls only. The pair-level communication data includes 12-month call records, from May 2003 to April 2004. In total we have 52,104 (4,342*12) pair-level observations. We include the descriptive statistics in Table 1. Since the tie strength in the previous month depends on the number of calls and the number of common contacts two months ago, we use the first two months of data to construct the lagged variables of tie strength – the tie strength of the first month. The data eventually used for estimation covers 10 months of activities, from July 2003 to April 2004, with 86,840 (4,342*2*10) individual level observations.

Our data contains three personal characteristics variables for each caller: age, gender, and VIP status. The sample includes users aged from 19 to 93. About 25% of them were female customers. The majority of customers were male customers because our sample was drawn from the VIP club that primarily targeted business users. There were four levels of statuses: Diamond, Gold, Silver, and Value. So Vip_i is a 3-by-1 vector indicating individual *i*'s VIP status in the calling plan. Specifically, if *i* is a Gold customer, $Vip_i = (1, 0, 0)$; if *i* is a Value customer, $Vip_i = (0, 0, 0)$. The privilege rank of the four levels of VIP status is Diamond > Gold > Silver > Value. In the data, the majority of individuals were Silver class (65%), followed by Value class (25%). Finally, on average, each pair shared 17 common contacts in the sample. On the monthly basis, each individual initiated an average of 12.5 calls with a total duration of 12.9 minutes each.

At the time a typical price plan consisted of a small monthly fee and a variable fee, possibly with some free minutes (it is more like a two-part tariff than a three-part tariff). For instance, one plan charged a fixed fee of RMB (Chinese Yuan) 30.00 and RMB 0.20 for each minute of usage. (The exchange rate was about 8.28 RMB for each 1 US dollar in the period between May 2003 and April 2004.) Since our sample consists of subscribers to the same service provider, all the calls were within the same wireless network. The average calling rate per minute was a little less than 0.20 RMB, or equivalently 0.024 $US at that time. There are two main sources of price variations. First, different consumers could subscribe to different plans. A plan with a higher fixed fee would typically correspond to a lower variable fee[2]. However, very few consumers changed the price plans during the observation period. Second, the firm provided various forms of discounts. For example, the firm designed different types of price plans and sometimes offered discounts for calls between users subscribing to the same type of price plans. Some consumers received promotional discounts, e.g. a 20% discount on the variable fees for being a loyal customer for more than three years. The price variables in our data were the true prices consumers paid for their calls, which were the net difference between the variable prices and the promotional discounts. To give an example, consider a consumer who subscribed to a plan with a variable fee of RMB 0.20 and received a 20% discount. Then this consumer's price would be equal to RMB 0.16 per minute.

We jointly estimate equations (1), (5), and (6) using the standard maximum likelihood method to maximize the following likelihood function

$$max_{\{a,bc,r,\rho,\sigma_1,\sigma_2\}}\, L = \prod_t \prod_{i,j} \Pr(q_{ij,t} = q_{ij,t}^{obs}, m_{ij,t} = m_{ij,t}^{obs} | e_1, e_2) \tag{8}$$

where for $q_{ij,t}^{obs} > 0$ and $\exp(m_{ij,t}^{obs}) > 0$, the probability is

$$\Pr(q_{ij,t} = q_{ij,t}^{obs}, m_{ij,t} = m_{ij,t}^{obs} | e_1, e_2) = pdf(e_1 = q_{ij,t}^{obs} - q_{ij,t}, e_2 = m_{ij,t}^{obs} - m_{ij,t} | \rho, \sigma_1, \sigma_2).$$

For zero observations ($q_{ij,t}^{obs} = 0$ and $\exp(m_{ij,t}^{obs}) = 0$), as in a Tobit model, we use the cumulative distribution function of the normally distributed error terms to calculate the probability. In our case, when the number of calls is zero, the duration of calls necessarily

[2] There might be an endogeneity problem here: heavy users choose plans with high fixed fees and low variable fees. Since we do not model consumer tariff choice, we may mistakenly attribute consumers' high call volumes to their low variable fees. We discuss this issue further in the Robustness Checks section.

becomes zero. Thus, the probability can be simplified from a bivariate normal CDF to a univariate normal CDF

$$\Pr\left(q_{ij,t}^{obs} = 0, \exp\left(m_{ij,t}^{obs}\right) = 0 \middle| e_1, e_2\right) = Pr\left(e_1 \le -q_{ij,t}\right) = cdf\left(e_1 \le -q_{ij,t}\right) = \Phi(-q_{ij,t}/\sigma_1)$$

The log likelihood function can be written as:

$$\sum_{q_{ij,t}^{obs}>0} \ln\left[pdf\left(e_1 = q_{ij,t}^{obs} - q_{ij,t}, e_2 = m_{ij,t}^{obs} - m_{ij,t} \middle| \rho, \sigma_1, \sigma_2\right)\right] + \sum_{q_{ij,t}^{obs}=0} \ln[\Phi(-q_{ij,t}/\sigma_1)]$$

Finally, in our setup, c_1, c_2 , r_1 in equation (1) cannot be separately identified from a_1 in equation (5) or b_1 in equation (6). In our actual estimation, we tried nine specifications with r_1=0.1, 0.2, 0.3, …, 0.9. The one with r_1=0.3 gave us the best model fit, thus we normalize r_1 to 0.3 and this is an implicit condition in the results reported below.

4. Estimation Results

In this section we present the estimation results for the parameters in equations (1), (5), (6), and (7). We use the observations in the first two months to construct the lagged tie strength variables ($s_{ij,1}$ and $s_{ij,2}$) and the observations from the 3rd to 12th month to estimate the parameters. We have experimented with a different number of months to construct the lagged tie strength variables and obtained very similar results. We present the estimation results in Table 2 for equation (1) regarding the tie strength dynamics, in Table 3 for equation (5) regarding the number of months, and in Table 4 for equation (6) regarding the number of minutes of calling. Overall the results are very consistent with our hypotheses. Note that we obtain our results after controlling for a positive correlation between two unobserved error terms in equations (5) and (6), specifically, ρ = 0.5188.

4.1 Tie Strength Dynamics

Table 2 shows the estimated results for the dynamics of tie strength. First, the estimate for c_1 is positive and statistically significant. Thus, the number of overlapping ties serves as a good predictor for the strength of tie. This result supports the transitivity property. Although we do not directly observe the relationships of any two individuals, in a probabilistic sense, two individuals with more common contacts have a better chance of being relatives, friends, or colleagues (strong ties) than just acquaintances (weak ties). The greater number of common contacts that two individuals share, the better they tend to know each other, the closer their relationship tends to be, and the stronger social tie they are likely to experience.

Second, the estimate for c_2 is positive and statistically significant. Thus, our results support the existence of the reciprocity effect. Specifically, if caller A initiated more calls to caller B in a particular month, then in the next month caller B's tie strength with caller A, and hence caller B's marginal utility of calling A, would increase. As a result, in the next month caller B would make more calls to caller A, possibly both in the frequency and duration of calls. This would then increase A's tie strength with B in the subsequent month and make more calls to B, and so on. The prediction from this dynamic reciprocity effect in another direction is that if A reduces the number of calls to B in the current period, B will make fewer phone calls to A in the next period. Afterwards if A does not initiate additional phone calls to B, their relationship will be significantly weakened in the long run.

4.2 Number of Calls

Table 3 presents the results of how the number of calls depends on the tie strength, prices, and the callers' characteristics. First, the estimate for a_1 is positive and statistically significant, which indicates that people made more phone calls to their stronger ties. Although a large part of the population had access to telecommunication services, each individual consumer's usage was concentrated within a limited section of the consumer's social circle. This concept is similar with the 80/20 rule that 80% of a firm's sales are derived from 20% of the firm's customer base. In personal communication, our results imply that people make most of their phone calls ("80%") to a very small proportion ("20%") of their contacts.

Second, both the estimates for a_2 and a_3 are negative and significant. Thus, both the incoming and outgoing prices matter in determining the number of calls from caller A to B. We also find that the absolute value of the estimate for a_2 is much larger than that for a_3 with a_2/a_3 =3.69. This implies that the outgoing prices matter more than the incoming prices on the number of calls. Relating to the collaborative utility framework described earlier, these results imply that both the initiating and the receiving caller's values of communications are weighed positively when determining the number of calls. Moreover, the higher weights are assigned to the initiating caller's value of communications. One of the implications of this result is the asymmetric calling behaviour between a pair of consumers. For example, suppose caller A pays a higher variable price on the outgoing calls than caller B. Given all other things being equal for these two consumers, caller B shall initiate more calls to A than A does to B. As a result, B will have a higher outgoing/incoming call ratio than A. While the negative effect of prices on the number of calls has been well documented, the literature has not distinguished the effects of outgoing and incoming calling prices. To the best of our knowledge, this is the first study that empirically demonstrates the different effects of outgoing and incoming prices on the number of calls.

Third, the number of calls initiated depends on the callers' characteristics. The results show that older customers made more calls but received fewer calls. This implies that the outgoing/incoming call ratio was higher for the older callers. The results also show that the callers' gender matters. Specifically, given all others the same, on average, the female customers made 0.80 more calls than the male customers in each month. But the effect of gender on the number of receiving calls was not significant. Finally, higher VIP-status customers made more calls. In terms of the number of phone calls being made, a diamond customer > a gold customer > a silver customer >a value customer. On average, a diamond/gold/silver customer makes 2.80/2.18/1.69 more phone calls in every month than a value customer, respectively.

4.3 Number of Calling Minutes

The results for the duration of calls are largely similar to the results for the number of calls. First, a positive and significant estimate for b_1 indicates that people spent more minutes in calling their strong ties. Thus, both the number of calls and the total calling minutes are good indicators for the strength of tie. Second, both estimates for b_2 and b_3 are negative and significant. Thus, the amount of calling time was lower when the initiating caller's outgoing price was higher and/or the receiving caller's incoming call price was higher. Interestingly, the absolute values of b_2 and b_3 are similar.

Third, similar to the results on the number of calls, compared to the younger customers, older customers made longer calls on a monthly basis. However, the calling minutes directed to the older customers were lower. Thus, the ratio of outgoing and incoming calling minutes was higher among older customers than younger customers. In the market there was an asymmetrically large flow of phone calls initiated by older callers. Gender is another personal characteristic that affects the amount of calling time. Given all others the same, there were more calling minutes both from and to female customers, thus the female customers spent more time talking on the phone overall. Finally, customers with higher VIP statuses talked for longer durations. Similar with the results on the number of calls, in terms of total amount of calling times initiated, a diamond customer > a gold customer > a silver customer > a value customer.

<u>4.4 Robustness Checks</u>

4.4.1 Add $m_{ji,t-1}$ to equation (1)

According to equation (1), $s_{ij,t}$ is a function of $n_{ij,t-1}$, $q_{ji,t-1}$, and $s_{ij,t-1}$. We do not include $m_{ji,t-1}$ in equation (1) because it is highly correlated with $q_{ji,t-1}$ - the correlation coefficient between the duration of calls and the number of calls is 0.8022. As a robustness check, we add $m_{ji,t-1}$ to equation (1):

$$s_{ij,t} = c_1 n_{ij,t-1} + c_2 q_{ji,t-1} + c_3 m_{ji,t-1} + r_1 s_{ij,t-1} \tag{1'}$$

We jointly estimate equations (1'), (5), (6), and (7). The results largely remain the same and they are reported in Tables A1-A3 in the appendix.

4.4.2 Allow $e_{1,ijt}$, $e_{1,jit}$, $e_{2,ijt}$, and $e_{2,jit}$ in equations (5) and (6) to be correlated

In equation (7), we only allow $e_{1,ijt}$ and $e_{2,ijt}$ (similarly, $e_{1,jit}$ and $e_{2,jit}$) to be correlated. We do not allow for correlation between $e_{1,ijt}$ and $e_{1,jit}$, or $e_{2,ijt}$ and $e_{2,jit}$. In other words, we allow the unobserved factor in the number of calls from *i* to *j* and the unobserved factor in the duration of calls from *i* to *j* to be correlated. But we do not allow the unobserved factor in the number/duration of calls from *i* to *j* and the unobserved factor in the number/duration of calls from *j* to *i* to be correlated. If there is within-dyad dependence, our estimates would be biased. To address this issue, we specify a more flexible error term structure:

$$\begin{pmatrix} e_{1,ijt} \\ e_{2,ijt} \\ e_{1,jit} \\ e_{2,jit} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \Sigma\right), \Sigma = \begin{pmatrix} \sigma_1{}^2 & \rho_{12}\sigma_1\sigma_2 & \rho_{13}\sigma_1\sigma_3 & \rho_{14}\sigma_1\sigma_4 \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2{}^2 & \rho_{23}\sigma_2\sigma_3 & \rho_{24}\sigma_2\sigma_4 \\ \rho_{13}\sigma_1\sigma_3 & \rho_{23}\sigma_2\sigma_3 & \sigma_3{}^2 & \rho_{34}\sigma_3\sigma_4 \\ \rho_{14}\sigma_1\sigma_4 & \rho_{24}\sigma_2\sigma_4 & \rho_{34}\sigma_3\sigma_4 & \sigma_4{}^2 \end{pmatrix} \qquad (7')$$

The estimation becomes more difficult with the new error term structure because now the main model is a multivariate Tobit model. Depending on whether $q_{ij,t}^{obs}>0$ and $q_{ji,t}^{obs}>0$, our likelihood function takes four different forms:

1. $q_{ij,t}^{obs}>0$, $q_{ji,t}^{obs}>0$

This is the simplest case. We can use the PDF of a multivariate normal distribution to define the likelihood:

$$\Pr\left(q_{ij,t} = q_{ij,t}^{obs}, m_{ij,t} = m_{ij,t}^{obs}, q_{ji,t} = q_{ji,t}^{obs}, m_{ji,t} = m_{ji,t}^{obs} \middle| e_{1,ijt}, e_{2,ijt}, e_{1,jit}, e_{2,jit}\right)$$

$$= pdf(e_{1,ijt} = q_{ij,t}^{obs} - q_{ij,t}, e_{2,ijt} = m_{ij,t}^{obs} - m_{ij,t}, e_{1,jit} = q_{ji,t}^{obs} - q_{ji,t}, e_{2,jit} = m_{ji,t}^{obs} - m_{ji,t}|\Sigma).$$

2. $q_{ij,t}^{obs}>0$, $q_{ji,t}^{obs}=0$

The likelihood can be defined sequentially: the probability of observing $q_{ij,t}^{obs}>0$ times the probability of observing $q_{ji,t}^{obs}=0$ conditional on $q_{ij,t}^{obs}>0$.

$$\Pr\left(q_{ij,t} = q_{ij,t}^{obs}, m_{ij,t} = m_{ij,t}^{obs}, q_{ji,t} = q_{ji,t}^{obs}, m_{ji,t} = m_{ji,t}^{obs} \middle| e_{1,ijt}, e_{2,ijt}, e_{1,jit}, e_{2,jit}\right)$$

$$= \Pr\left(q_{ij,t} = q_{ij,t}^{obs}, m_{ij,t} = m_{ij,t}^{obs}, q_{ji,t}^{obs} = 0 \middle| e_{1,ijt}, e_{2,ijt}, e_{1,jit}\right)$$

$$= pdf\left(e_{1,ijt} = q_{ij,t}^{obs} - q_{ij,t}, e_{2,ijt} = m_{ij,t}^{obs} - m_{ij,t} \middle| \Sigma_{1,2}\right)$$

$$* \Pr(e_{1,jit} \leq -q_{ji,t} | e_{1,ijt} = q_{ij,t}^{obs} - q_{ij,t}, e_{2,ijt} = m_{ij,t}^{obs} - m_{ij,t}, \Sigma_{12,3}),$$

where $\Pr\left(e_{1,jit} \leq -q_{ji,t} \middle| e_{1,ijt} = q_{ij,t}^{obs} - q_{ij,t}, e_{2,ijt} = m_{ij,t}^{obs} - m_{ij,t}, \mu_{12,3}, \sigma_{12,3}\right)$

$$= cdf\left(-q_{ji,t} \middle| \mu_{12,3}, \sigma_{12,3}\right) = \Phi(-q_{ij,t} - \mu_{12,3}/\sigma_{12,3}),$$

$$\Sigma_{1,2} = \begin{pmatrix} {\sigma_1}^2 & \rho_{12}\sigma_1\sigma_2 \\ \rho_{12}\sigma_1\sigma_2 & {\sigma_2}^2 \end{pmatrix},$$

$$\mu_{12,3} = [\rho_{13}\sigma_1\sigma_3, \rho_{23}\sigma_2\sigma_3] * inv\left(\Sigma_{1,2}\right) * [q_{ij,t}^{obs} - q_{ij,t}, m_{ij,t}^{obs} - m_{ij,t}]',$$

$$\sigma_{12,3} = \sigma_3 - [\rho_{13}\sigma_1\sigma_3, \rho_{23}\sigma_2\sigma_3] * inv\left(\Sigma_{1,2}\right) * [\rho_{13}\sigma_1\sigma_3, \rho_{23}\sigma_2\sigma_3]'.$$

3. $q_{ij,t}^{obs}$=0, $q_{ji,t}^{obs}$>0

Case 3 is similar to case 2. We omit the equations to avoid repetition.

4. $q_{ij,t}^{obs}$=0, $q_{ji,t}^{obs}$=0

$$\Pr\left(q_{ij,t} = q_{ij,t}^{obs}, m_{ij,t} = m_{ij,t}^{obs}, q_{ji,t} = q_{ji,t}^{obs}, m_{ji,t} = m_{ji,t}^{obs} \middle| e_{1,ijt}, e_{2,ijt}, e_{1,jit}, e_{2,jit}\right)$$

$$= \Pr\left(q_{ij,t}^{obs} = 0, q_{ji,t}^{obs} = 0 \middle| \Sigma_{1,3}\right) = Pr\left(e_{1,ijt} \leq -q_{ij,t}, e_{1,jit} \leq -q_{ji,t} | \Sigma_{1,3}\right),$$

$$\text{where } \Sigma_{1,3} = \begin{pmatrix} {\sigma_1}^2 & \rho_{13}\sigma_1\sigma_3 \\ \rho_{13}\sigma_1\sigma_3 & {\sigma_3}^2 \end{pmatrix}$$

The probability is given by a bivariate normal CDF, which cannot be directly obtained. We simulate bivariate normal distributions via the GHK simulator to calculate the probability for this case. Thus our estimation method becomes simulated maximum likelihood.

We jointly estimate equations (1'), (5), (6), and (7'). The results are reported in Tables A4-A6 in the appendix. The qualitative properties of the results are largely the same. We do find significant and positive correlations between the unobserved factors within a dyad (all pho's are significant and positive).

4.4.3 Add individual-level fixed effects to the duration of calls regression

Our model may suffer an endogeneity problem because the heavy users could choose plans with high fixed fees and low variable fees in order to save the total cost. As a result, we may mistakenly attribute consumers' high call volumes to their low variable fees without modeling consumer tariff choice. In other words, consumers may not be responding to price promotions; the negative correlation between price and calling volume could be an outcome of endogenous tariff choice. To at least partially address this issue, we estimate one fixed-effect model with the caller as the panel variable, and another fixed-effect model with the receiver as the panel variable[3]. By eliminating unobserved individual heterogeneity (including the cross-sectional variation on price plan selection), we can test, conditional on the price plan chosen, whether consumers are indeed sensitive to price changes.

The results are reported in Tables A7-A8 in the appendix. After we add fixed effects to callers, the outgoing call price coefficient remains significant and negative. Interestingly, the incoming call price coefficient becomes insignificant. These results indicate that the caller is

[3] We did not add fixed effects at the pair level because the price plan is chosen by individuals after considering all their social contacts. The price plan choice is not a dyad-level decision.

indeed responsive to the outgoing call price, but may not know or care too much about the receiver's incoming call price. Similarly, after we add fixed effects to receivers, the incoming call price coefficient is significant and negative, while the outgoing call price coefficient becomes insignificant. These results imply that the receiver is sensitive to the incoming call price, but may not know or care about the caller's outgoing call price. These results combined seem to support the assumption that the pair level calling decision is a joint decision made by both the initiating caller and the receiver, while the caller mainly cares about the outgoing call price and the receiver mainly cares about the incoming call price. The fixed-effect model results also show that consumers are responsive to price changes - the negative correlation between price and calling volume is not simply driven by endogenous tariff choice[4].

5. Marketing Implications

Our main estimation results are obtained from equations (5) and (6). As we have demonstrated in section 2, these demand equations are essentially the equilibrium conditions in a utility maximization model. Thus the parameters being estimated are transformed micro-parameters. The structural nature of the model allows us to conduct counterfactual experiments to evaluate the marketing implications, specifically in measuring the return of temporary price promotions and in designing the profit-maximizing price plans.

[4] Nevertheless, we cannot add fixed effects to our main empirical specification for two reasons. First, our empirical specification is derived from a collaborative utility framework. The model coefficients have clear economic meanings and we need them to calculate firm revenues and do counter-factual experiments. Adding fixed effects would make it difficult to interpret the meanings of model coefficients. Second, our model is a simultaneous equation model. Technically, we could not add fixed effects to equation (1) because $s_{ij,t}$ is not directly observed.

5.1 Evaluate the Return of a Temporary Price Promotion: Outgoing and Incoming Calls

In the introduction section, we described one important distinction between the grocery product market and the wireless service market: while a price promotion on laundry detergents can affect only the target households' purchase decisions, a price promotion on wireless phone service would increase not only the target households' outgoing calls but also the resulting incoming calls of their social contacts. When consumers need to pay for incoming calls, a wireless service provider would underestimate the return of a price promotion if limiting its attention only to the target households' outgoing calls and ignoring the domino effect on the incoming calls of their networks.

To demonstrate how much revenue would be overlooked if one focuses on only the outgoing calls, we conduct the following counterfactual experiments based on the estimation results given in Tables 2-4. Consider a one-time price promotion applied to all of our panel consumers' outgoing call prices in month 3. We first calculate the total revenue changes in months 3-12 from both the outgoing calls and the incoming calls predicted by our model [equations (1), (5), and (6)]. We then calculate the revenue changes in months 3-12 from the outgoing calls only. Taking the difference between these two amounts of revenue changes, we can obtain the magnitude of overlooked revenues. We provide in Table 5 the detailed results corresponding to different levels of price promotions. For example, with a 90% promotion on the outgoing call price while keeping the incoming call price unchanged, we could miss the revenue of $431.23 from the increased incoming calls if focusing only on the outgoing calls.

Similarly, we estimate how much revenue would be overlooked if we focus on consumers' incoming calls only. Again, consider a one-time price promotion applied to all of our consumers' incoming call prices in month 3. We first calculate the total revenue changes in months 3-12 from both the outgoing calls and the incoming calls predicted by our model. We then calculate the revenue changes in months 3-12 from the incoming calls only. Taking the difference between these two amounts of changes, we obtain the magnitude of overlooked revenue. We provide the detailed results in Table 6 for different levels of promotions. For example, for a 90% promotion on the incoming call price while keeping the outgoing call price unchanged, we would miss the revenue of $274.72 from the increased outgoing calls if we ignore the revenue from the outgoing calls.

Clearly the counterfactual exercises demonstrate that a firm could underestimate the effect of a temporary price promotion if the firm focuses on only the service under promotion (e.g. the outgoing calls). The nature of joint consumption implies that the price promotion also affects the consumption of the service not under promotion (e.g. the incoming calls). In this counterfactual exercise we include the entire sample for the hypothetical price promotion. The overlooked revenue is expected to be much more substantial if the temporary price promotion covers only a subset of the sample.

5.2 Evaluate the Long-Term Return of a Temporary Price Promotion: the Reciprocity Effect

As explained in section 2, there is a reciprocity effect in people's calling decisions according to equation (1). If a firm offers a temporary price promotion, the reciprocal effect is expected to increase the firm's total revenues in the subsequent time periods. Specifically, for a pair of individuals *i* and *j*, if the firm runs a price promotion in time *t-1* on *j*'s outgoing call price or *i*'s incoming call price, *j* would call *i* more (reflected by larger $q_{ji,t-1}$ and $m_{ji,t-1}$) in $t-1$. Then, larger $q_{ji,t-1}$ → stronger $s_{ij,t}$ → larger $q_{ij,t}$ → stronger $s_{ji,t+1}$ → larger $q_{ji,t+1}$ → …

To demonstrate the implications of this reciprocity effect, we consider a one-time price promotion offered in month 3. We first calculate the total revenue from months 3-12 predicted by our model, and we then calculate the total revenue predicted by a benchmark model without the dynamic reciprocity effect. In the benchmark model, the promotion only affects the consumers' calling behaviour in month 3 and there is no carry-over effect. We compute the total revenue differences for different levels of price discounts and present the results in Table 7. The total revenue would be generally underestimated by several hundred dollars if we ignore the dynamic reciprocity effect. For example, for a 50% promotion on both the outgoing call price and the incoming call price, the promotional effect on the total revenues in months 4-12 would be underestimated by $384.17 if we ignore the reciprocity effect.

The reciprocity effect underlines a new source of long-term effects for a price promotion. In the packaged goods market, a price promotion may also have long-term effects on sales through repeat purchases. Such long-term effects are typically driven by the changes in the consumers' brand awareness and loyalty and switching costs (e.g., Blattberg, Briesch, and Fox 1995). In contrast, what changes with the reciprocity effect is consumers' relationship with their social contacts, not their relationship with the brands. The long-term sales effect resulting from the reciprocity factor is realized through the nature of consumption externality and the dynamic aspect of reciprocity.

5.3 Optimal 2-sided Pay Scheme: Incoming Call and Outgoing Call Prices

Our model has useful implications to the optimal design of 2-sided pay schemes with different prices on the incoming and outgoing calls. The incoming calls are typically free for the fixed-line phones but are often charged like the outgoing calls for the wireless phones. Analytical research has been conducted to study the welfare implications of the "receiver-pay principle" (e.g., Jeon, Laffont, and Tirole 2004). To illustrate the implications of our model to the design of pricing plans, we conduct two simulation exercises. First, we search for the optimal 3rd-period prices that maximize the firm's revenue from the sample consumers. We consider a set of price deviations from the actual outgoing call and incoming call prices in the 3rd month. Based on the results in Tables 2-4, we simulate the effects of these price changes on the total revenue from the entire sample in months 3-12. Figure 1 displays the predicted total revenue as a function of the outgoing call price change and incoming call price change. The revenue-maximizing prices are positive and higher than the actual prices for both the incoming and outgoing calls. There are two possible explanations for this result. First, our model does not consider the competition between service providers. Second, our sample consists of only the VIP customers who were not very price sensitive. The optimal prices would be lower if we had more low-volume customers who tended to be more price-sensitive.

Second, in order to search for situations where a firm may provide free incoming calls we increase the coefficients of the outgoing call prices (a_2 and b_2) by 400% and the coefficients of the incoming call prices (a_3 and b_3) by 900%. As illustrated by Figure 2, the shape of the revenue function became completely different from the one in Figure 1. Now the optimal pricing strategy to maximize revenues from months 3-12 would be to increase the outgoing call prices by 82.74% while reducing the incoming call prices by 100% (numbers obtained through numerical optimization), which would essentially give customers free incoming calls. Interestingly, as the receiver's incoming call price becomes sufficiently important in determining the number of calls, the "no receiver-pay" principle could be optimal. When the consumers really care about the receiving callers' prices, giving consumers free incoming calls could cause them to call each other more often and this will bring firms higher revenues.

6. Conclusion

This paper investigates consumers' calling behaviour from the social network perspective. We employ a unique wireless communication panel dataset with detailed information on who called who, the number and duration of calls, the incoming and outgoing prices for each call, and the callers' personal characteristics. We propose an economic framework for how consumers decide their calling activities in a collaborative fashion to maximize the weighted average of two callers' value of communications. We derive and estimate a model for the number and the duration of calls between a pair of consumers with dynamic tie strength. Our empirical results validate that, first, the tie strength increased with the number of common contacts. Second, people initiated more calls and spent more time talking to their strong ties. Third, the reciprocal effect existed in this market. Specifically, consumer (A)'s tie strength with another consumer (B) increased with the number of calls A received from B in the previous period. A stronger social tie would in turn prompt consumer B to call A more often subsequently. We also find that the outgoing prices mattered much more than the incoming prices on the number of calls. Thus, the initiating caller's value function weighed more than the receiving caller's value function in determining the number of calls. Based on our estimation results, we use simulations to illustrate the marketing implications in evaluating the effect of a temporal price promotion and in designing service price plans. We find that the absence of the social network perspective could lead to an underestimation of both short-term and long-term returns of a price promotion. We also find that when the receiving consumers' value of communications enjoys a large weight in determining the calling activities, firms may find it optimal to offer free incoming calls - the no-receiver pay principle.

Our paper is subject to a potential sample selection problem. The sample we selected in this paper might be biased because we did not include those unrealized ties – ties where communications could have potentially occurred but did not. There are three reasons why we did not correct the selection bias. First, our network has 38,000 nodes and hence 1,444/2 million pairs of customers. It is technically not feasible to deal with such a large sample. Second, although it is theoretically possible that any two consumers can be connected, in reality each consumer lives in a small circle and communicates with a very small number of people. The ties between most of those 1,442/2 pairs would never be realized. Third, previous research shows that only focusing on realized ties does not substantially reduce statistical power (e.g., Coslett, 1981; Imbens, 1992; Sorenson and Stuart, 2008). Fourth, the main focus of our paper is to show that it is important to incorporate social network characteristics in the study of telecommunications markets. We do not intend to generalize our quantitative results to other cases. To some extent one could consider our study focusing on heavy users only. Finally, generalizing to the entire population does not have much practical value because the firm earns its revenues primarily from the heavy users – the pairs with frequent conversations. Any social network-based marketing schemes would target only these pairs with strong ties.

Our paper provides the first empirical study incorporating social network characteristics in modeling consumer's economic behaviour. Future research may extend the framework from the dyad level to multiple-player networks. This extension would allow a model to capture additional properties of network dynamics. Another direction of future research is to study the relation between all the ties connected to one individual consumer. This extension would facilitate a better understanding of how a consumer substitutes communications from one contact to another.

Table 1 Two-sided Descriptive Statistics (Number of pair-level observations = 52,104)

	Side 1				Side 2			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Number of outgoing calls	12.531	20.026	0	312	12.489	20.874	0	612
Minutes of outgoing calls	12.857	26.875	0	1301.9	12.886	27.680	0	913.1
Unit outgoing price (Chinese cent/minute)	19.310	9.094	0	60	19.108	8.876	0	60
Unit incoming price (Chinese cent/minute)	19.094	9.272	0	60	18.909	9.029	0	60
Caller age	37.974	7.378	19	93	37.862	7.074	19	82
Caller gender (female)	0.249	0.432	0	1	0.2655	0.441	0	1
Vip G (value)	0.247	0.431	0	1	0.257	0.437	0	1
Vip J (gold)	0.090	0.287	0	1	0.089	0.286	0	1
Vip Y (silver)	0.650	0.477	0	1	0.642	0.479	0	1
Vip Z (diamond)	0.012	0.110	0	1	0.012	0.108	0	1
Number of overlap contacts	17.152	14.739	0	165				

Table 2 Estimation Results for Tie Strength Dynamics ($s_{ij,t}$)

Parameter	Variable	Parameter estimate	Standard error	z-value
c_1	Number of overlapping ties (Lag 1 month)	**0.0567**	0.0019	29.7553
c_2	Number of Incoming calls (Lag 1 month)	**0.2605**	0.0014	182.8011
r_1	Tie strength (Lag 1 month)	0.3	n.a.	n.a.

Bold: significant at 5% level; +: significant at 10% level

Table 3 Estimation Results for Number of Calls from *i* to *j*

Parameter	Variable	Parameter estimate	Standard error	z-value
a_0	Intercept	**-3.6556**	0.4764	7.6729
a_1	Tie_strength$_{ij}$	**1.8913**	0.0068	279.5763
a_2	i's unit outgoing price	**-0.0579**	0.0069	8.3908
a_3	j's unit incoming price	**-0.0157**	0.0067	2.3262
a_X	i's age	**0.1134**	0.0088	12.8862
a_X	j's age	**-0.0392**	0.0084	4.6678
a_X	i's gender (female)	**0.7993**	0.1594	5.0149
a_X	j's gender (female)	0.1191	0.1452	0.8205
a_X	i's VIP status_J	**2.1845**	0.2517	8.6806
a_X	i's VIP status_Y	**1.6880**	0.1469	11.4873
a_X	i's VIP status_Z	**2.8000**	0.5705	4.9077
a_X	j's VIP status_J	**-1.2401**	0.236	5.2542
a_X	j's VIP status_Y	-0.0806	0.1427	0.5646
a_X	j's VIP status_Z	**-4.0823**	0.5759	7.0891
ρ		**0.5188**	0.003	174.1659
σ_1		**16.8361**	0.0447	376.7899
σ_2		**1.2885**	0.0032	403.0172
-Log(Likelihood)		434,582.7		

Bold: significant at 5% level; +: significant at 10% level

Table 4 Estimation Results for Minutes of Calls from *i* to *j*

Parameter	Variable	Parameter estimate	Standard error	z-value
b_0	Intercept	**4.9112**	0.0351	139.8514
b_1	Tie_strength$_{ij}$	**0.0893**	0.0005	182.1042
b_2	*i*'s unit outgoing price	**-0.0026**	0.0005	4.8145
b_3	*j*'s unit incoming price	**-0.0032**	0.0005	5.9564
b_X	*i*'s age	**0.0062**	0.0007	9.1275
b_X	*j*'s age	**-0.0030**	0.0007	4.246
b_X	*i*'s gender (female)	**0.0911**	0.0126	7.2559
b_X	*j*'s gender (female)	**0.0777**	0.0116	6.7177
b_X	*i*'s VIP status_J	**0.2879**	0.0204	14.0979
b_X	*i*'s VIP status_Y	**0.2089**	0.0114	18.3197
b_X	*i*'s VIP status_ Z	**0.3308**	0.0465	7.1183
b_X	*j*'s VIP status_J	**0.0661**	0.0191	3.4615
b_X	*j*'s VIP status_Y	**0.0721**	0.0122	5.922
b_X	*j*'s VIP status_Z	**-0.2042**	0.0464	4.3994

Bold: significant at 5% level; +: significant at 10% level

Table 5 Overlooked Revenues from the Increased Incoming Calls*

percent1\percent2**	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1	0
-0.9	293.68	309.93	325.94	341.70	357.21	372.49	387.53	402.31	416.88	431.23
-0.8	260.75	275.15	289.34	303.27	317.03	330.57	343.90	357.02	369.94	382.66
-0.7	227.86	240.43	252.81	264.99	276.99	288.81	300.44	311.89	323.16	334.25
-0.6	195.09	205.83	216.41	226.82	237.07	247.17	257.11	266.90	276.53	286.01
-0.5	162.38	171.31	180.10	188.75	197.27	205.66	213.92	222.05	230.06	237.94
-0.4	129.76	136.88	143.89	150.79	157.59	164.28	170.87	177.35	183.74	190.03
-0.3	97.21	102.53	107.77	112.94	118.02	123.02	127.95	132.80	137.58	142.28
-0.2	64.73	68.27	71.75	75.19	78.56	81.89	85.17	88.39	91.57	94.69
-0.1	32.33	34.09	35.83	37.54	39.23	40.88	42.52	44.12	45.71	47.26

* This table measures the overlooked revenues from the increased incoming calls due to a temporary price promotion on the outgoing calls in month 3. The revenues could be overlooked if examining only the type of calls (outgoing calls) on promotion. It is computed in dollars and calculated as the total revenue change from the increased incoming calls in months 3-12 due to a one-time price promotion on the outgoing call price in month 3 (percent 1), at different levels of the incoming call prices in month 3 (percent 2). For example, with the incoming call price same as actual (percent2=0), for a 90% discount on the outgoing call price (percent1=-0.9), there would be $431.23 revenue increase due to the increased incoming calls. This is the amount that would be overlooked if one ignores the revenues from the incoming calls when evaluating the return of the temporary price promotion in month 3. For another example, consider a 50% discount on the outgoing call price (percent1=-0.5) and set the incoming call price as low as 50% of actual price (percent2=-0.5). The increased revenue from the incoming calls would be $197.27; again this would be the overlooked revenue if one focuses on only the outgoing calls when evaluating the return of the price promotion.

**New outgoing call price = actual outgoing call price×(1+percent1)
New incoming call price = actual incoming call price×(1+percent2)

Table 6 Overlooked Revenue from the Increased Outgoing Calls *

percent1\percent2	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1
-0.9	94.89	84.27	73.66	63.08	52.52	41.99	31.47	20.92	10.45
-0.8	115.83	102.81	89.82	76.82	63.91	51.05	38.23	25.45	12.70
-0.7	136.47	121.07	105.73	90.46	75.24	60.08	44.97	29.92	14.93
-0.6	156.92	139.18	121.52	103.94	86.43	68.99	51.63	34.35	17.14
-0.5	177.14	157.08	137.12	117.26	97.49	77.81	58.22	38.72	19.32
-0.4	197.12	174.77	152.54	130.43	108.42	86.52	64.73	43.05	21.47
-0.3	216.86	192.26	167.78	143.44	119.22	95.13	71.16	47.32	23.60
-0.2	236.38	209.54	182.85	156.30	129.90	103.64	77.52	51.54	25.70
-0.1	255.66	226.61	197.73	169.01	140.45	112.04	83.80	55.71	27.78
0	274.72	243.49	212.44	181.57	150.87	120.35	90.01	59.83	29.83

* This table measures the overlooked revenues from the increased outgoing calls due to a temporary price promotion on the incoming calls in month 3. The revenues could be overlooked if examining only the type of calls (incoming calls) on promotion. It is computed in dollars and calculated as the total revenue change from the increased outgoing calls in months 3-12 due to a one-time price promotion on the incoming call price in month 3 (percent 2), at different levels of the outgoing call prices in month 3 (percent 1). For example, with the outgoing call price same as actual (percent1=0), for a 90% discount on the incoming call price (percent2=-0.9), there would be $274.72 revenue increase due to the increased outgoing calls. This is the amount that would be overlooked if one ignores the revenues from the outgoing calls when evaluating the return of the temporary price promotion in month 3. For another example, consider a 50% discount on the incoming call price (percent2=-0.5) and set the outgoing call price as low as 50% of actual price (percent1=-0.5). The increased revenue from the outgoing calls would be $97.49; again this would be the overlooked revenue if one focuses on only the incoming calls when evaluating the return of the price promotion on the incoming calls.

** New outgoing call price = actual outgoing call price×(1+percent1)
New incoming call price = actual incoming call price×(1+percent2)

Table 7 Revenue Difference Due to Reciprocity Effect*

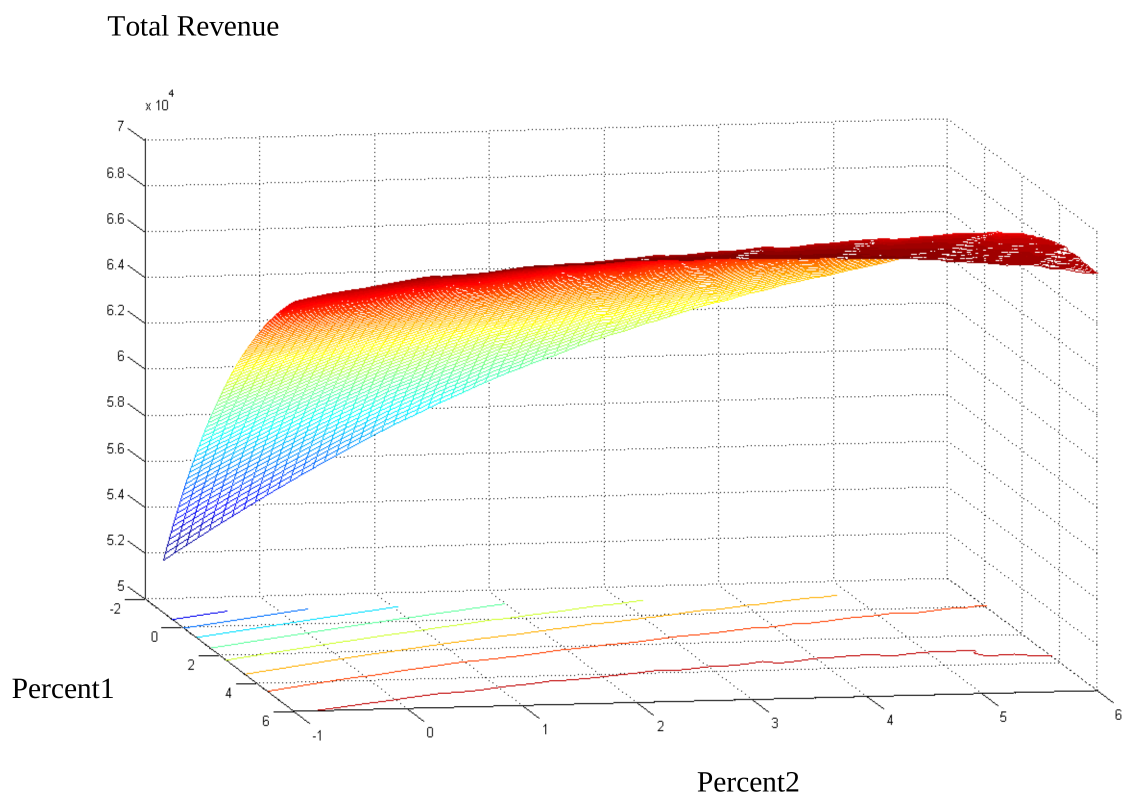
percent1\percent2**	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1
-0.9	695.10	679.03	662.96	646.90	630.85	614.81	598.77	582.66	566.64
-0.8	633.15	617.10	601.06	584.94	568.92	552.91	536.91	520.91	504.93
-0.7	571.22	555.21	539.20	523.20	507.21	491.23	475.26	459.30	443.34
-0.6	509.51	493.53	477.56	461.59	445.63	429.68	413.74	397.81	381.88
-0.5	447.93	431.98	416.04	400.10	384.17	368.26	352.35	336.44	320.55
-0.4	386.48	370.56	354.64	338.74	322.84	306.95	291.07	275.20	259.34
-0.3	325.15	309.26	293.37	277.50	261.63	245.78	229.93	214.09	198.25
-0.2	263.94	248.08	232.23	216.38	200.55	184.72	168.90	153.09	137.29
-0.1	202.86	187.03	171.21	155.39	139.59	123.79	108.00	92.22	76.45

* This table measures the difference in revenue from a temporary price promotion in month 3 due to the reciprocity effect. The revenue difference is measured in dollars and calculated as the difference between the total revenues from months 3-12 as predicted by two different models: the model with reciprocity effect as estimated in the paper and the model without reciprocity effect (i.e., $s_{ij,4}$ does not change despite a larger $q_{ji,3}$). For example, consider a 50% price discount for both the outgoing call price and the incoming call price (percent1=-0.5, percent2=-0.5). The table shows that the reciprocity effect would lead to an additional revenue increase of $384.17 due to more phone exchanges after month 3.

** New outgoing call price = actual outgoing call price*(1+percent1)
New incoming call price = actual incoming call price*(1+percent2)

Figure 1 Total Revenues from Months 3-12 as a Function of Price Changes in Month 3

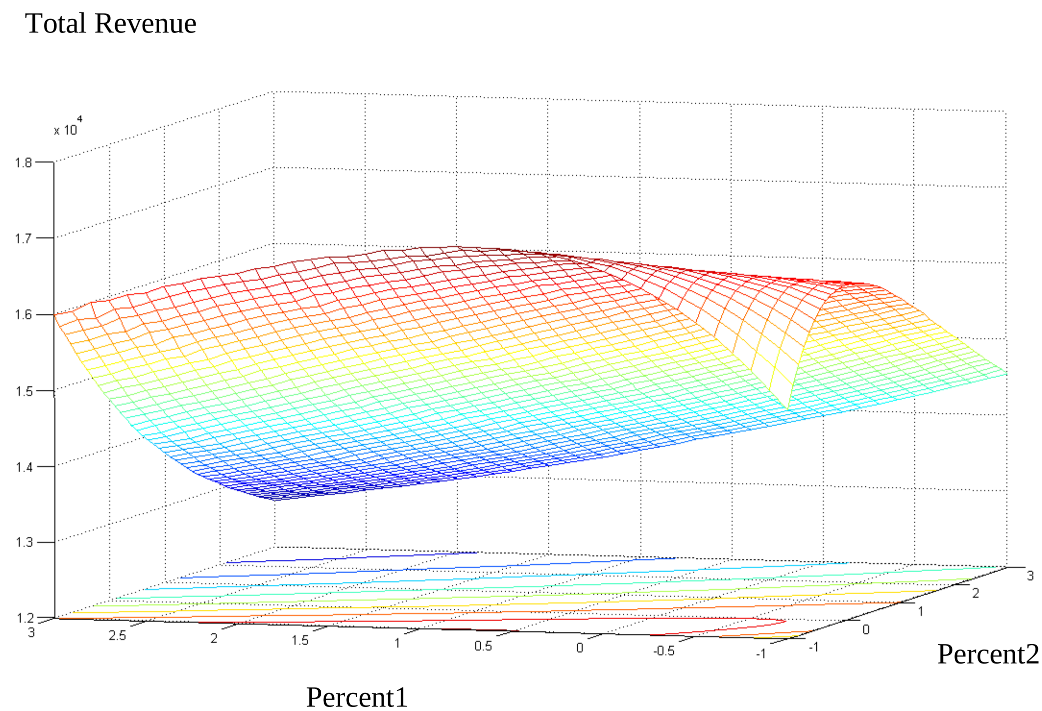
(Measured in Dollars with Price Sensitivities Based on Actual Data)



*New outgoing call price = actual outgoing call price×(1+percent1)
New incoming call price = actual incoming call price×(1+percent2)

Figure 2 Total Revenues from Months 3-12 as a Function of Price Changes in Month 3

(Measured in Dollars and Hypothetical Price Sensitivities)*



New outgoing call price = actual outgoing call price(1+percent1)
New incoming call price = actual incoming call price*(1+percent2)
Price sensitivities: the coefficients of the outgoing call prices (a_2 and b_2) increased by 400% and the coefficients of the incoming call prices (a_3 and b_3) increased by 900%.

Appendix

Table A1 Estimation Results for Tie Strength Dynamics ($s_{ij,t}$)

Parameter	Variable	Parameter estimate	Standard error	z-value
c_1	Number of overlapping ties (Lag 1 month)	**0.0438**	0.0019	23.6077
c_2	Number of Incoming calls (Lag 1 month)	**0.2358**	0.0018	129.5259
c_3	Duration of Incoming calls (Lag 1 month)	**0.7115**	0.0143	49.8474
r_1	Tie strength (Lag 1 month)	0.3	n.a.	n.a.

Bold: significant at 5% level; +: significant at 10% level

Table A2 Estimation Results for Number of Calls from *i* to *j*

Parameter	Variable	Parameter estimate	Standard error	z-value
a_0	Intercept	**-9.6831**	0.4866	19.8977
a_1	Tie_strength$_{ij}$	**1.7611**	0.006	291.6353
a_2	i's unit outgoing price	**-0.0564**	0.0076	7.3739
a_3	j's unit incoming price	-0.0127+	0.0074	1.7044
a_X	i's age	**0.1064**	0.0093	11.4265
a_X	j's age	**-0.0555**	0.0089	6.2472
a_X	i's gender (female)	**0.8028**	0.1504	5.3367
a_X	j's gender (female)	0.2136	0.1497	1.4269
a_X	i's VIP status_J	**2.1813**	0.2575	8.4701
a_X	i's VIP status_Y	**1.5915**	0.1512	10.5291
a_X	i's VIP status_Z	**3.3381**	0.5988	5.5746
a_X	j's VIP status_J	**-1.405**	0.2535	5.5422
a_X	j's VIP status_Y	-0.2547+	0.1505	1.6922
a_X	j's VIP status_Z	**-3.897**	0.614	6.3472
ρ		**0.4936**	0.0031	158.7762
σ_1		**16.8414**	0.0468	359.8871
σ_2		**1.2568**	0.0035	362.6856
-Log(Likelihood)		433,452.0		

Bold: significant at 5% level; +: significant at 10% level

Table A3 Estimation Results for Minutes of Calls from *i* to *j*

Parameter	Variable	Parameter estimate	Standard error	z-value
b_0	Intercept	**4.5605**	0.0355	128.4946
b_1	Tie_strength$_{ij}$	**0.0896**	0.0005	176.6817
b_2	*i*'s unit outgoing price	**-0.0022**	0.0005	4.0005
b_3	*j*'s unit incoming price	**-0.0026**	0.0006	4.7541
b_X	*i*'s age	**0.0060**	0.0007	8.3904
b_X	*j*'s age	**-0.0039**	0.0007	5.8066
b_X	*i*'s gender (female)	**0.0854**	0.0123	6.9543
b_X	*j*'s gender (female)	**0.0755**	0.0122	6.1823
b_X	*i*'s VIP status_J	**0.2778**	0.0208	13.3391
b_X	*i*'s VIP status_Y	**0.1976**	0.0125	15.7506
b_X	*i*'s VIP status_ Z	**0.3559**	0.049	7.2594
b_X	*j*'s VIP status_J	**0.0421**	0.0203	2.0687
b_X	*j*'s VIP status_Y	**0.0539**	0.0127	4.2334
b_X	*j*'s VIP status_Z	**-0.2098**	0.0502	4.1774

Bold: significant at 5% level; +: significant at 10% level

Table A4 Estimation Results for Tie Strength Dynamics ($s_{ij,t}$)

Parameter	Variable	Parameter estimate	Standard error	z-value
c_1	Number of overlapping ties (Lag 1 month)	**0.1203**	0.0015	80.9931
c_2	Number of Incoming calls (Lag 1 month)	**0.8181**	0.0412	19.8511
c_3	Duration of Incoming calls (Lag 1 month)	**0.5345**	0.042	12.7374
r_1	Tie strength (Lag 1 month)	0.3	n.a.	n.a.

Bold: significant at 5% level; +: significant at 10% level

Table A5 Estimation Results for Number of Calls from *i* to *j*

Parameter	Variable	Parameter estimate	Standard error	z-value
a_0	Intercept	-0.4046	0.4714	0.8583
a_1	Tie_strength$_{ij}$	**0.5475**	0.0277	19.7556
a_2	i's unit outgoing price	**-0.043**	0.007	6.1204
a_3	j's unit incoming price	**-0.0209**	0.0069	3.0219
a_X	i's age	**0.0788**	0.0083	9.5342
a_X	j's age	**-0.0444**	0.0083	5.373
a_X	i's gender (female)	**0.331**	0.1337	2.4762
a_X	j's gender (female)	0.1243	0.1335	0.9306
a_X	i's VIP status_J	0.3112	0.2244	1.3869
a_X	i's VIP status_Y	**0.472**	0.1368	3.451
a_X	i's VIP status_Z	0.133	0.5247	0.2535
a_X	j's VIP status_J	-0.1493	0.2242	0.6658
a_X	j's VIP status_Y	0.1976	0.1367	1.4454
a_X	j's VIP status_Z	-0.0908	0.5307	0.1711
σ_1		**16.426**	0.0614	267.7194
σ_2		**1.3599**	0.0051	266.7344
σ_3		**17.7133**	0.0623	284.2122
σ_4		**1.3659**	0.0051	266.0362
pho12		**0.526**	0.0038	139.4965
pho13		**0.0383**	0.007	5.5008
pho23		**0.2569**	0.004	64.6383
pho14		**0.0655**	0.0045	14.7055
pho24		**0.4551**	0.0041	111.4464
pho34		**0.5668**	0.0034	167.9006
-Log(Likelihood)		431,795.9		

Bold: significant at 5% level; +: significant at 10% level

Table A6 Estimation Results for Minutes of Calls from *i* to *j*

Parameter	Variable	Parameter estimate	Standard error	z-value
b_0	Intercept	**4.9748**	0.0445	111.7566
b_1	Tie_strength$_{ij}$	**0.0238**	0.0012	19.8139
b_2	*i*'s unit outgoing price	**-0.0034**	0.0005	6.0992
b_3	*j*'s unit incoming price	**-0.0038**	0.0005	7.0241
b_X	*i*'s age	**0.0057**	0.0007	8.5715
b_X	*j*'s age	**-0.0025**	0.0007	3.7135
b_X	*i*'s gender (female)	**0.0724**	0.0112	6.4721
b_X	*j*'s gender (female)	**0.0762**	0.0112	6.8157
b_X	*i*'s VIP status_J	**0.2445**	0.0185	13.2107
b_X	*i*'s VIP status_Y	**0.176**	0.0114	15.5025
b_X	*i*'s VIP status_ Z	**0.2929**	0.0448	6.5415
b_X	*j*'s VIP status_J	**0.116**	0.0185	6.2559
b_X	*j*'s VIP status_Y	**0.0897**	0.0114	7.8978
b_X	*j*'s VIP status_Z	-0.0791+	0.0449	1.7605

Bold: significant at 5% level; +: significant at 10% level

Table A7 Fixed-Effect Model for Minutes of Calls from *i* to *j* (Panel Variable: Caller *i)**

Variable	Coef.	Std. Err.	t
i's unit outgoing price	**-2.249**	0.839	2.68
j's unit incoming price	-1.031	0.659	1.56
Number of overlapping ties (Lag 1 month)	**30.888**	0.390	79.17
j's age	**-6.587**	0.958	6.87
j's gender (female)	**150.386**	14.435	10.42
j's VIP status_J	**74.493**	20.086	3.71
j's VIP status_Y	**42.626**	13.333	3.2
j's VIP status_Z	**-149.241**	43.560	3.43
Intercept	**484.081**	41.552	11.65
R-sq (within)	0.0703		
R-sq (between)	0.0461		
R-sq (overall)	0.0498		
Number of obs	95524		
Number of groups	5475		

Bold: significant at 5% level; +: significant at 10% level
* fixed effects added to caller *i*

Table A8 Fixed-Effect Model for Minutes of Calls from *i* to *j* (Panel Variable: Receiver *j)**

Variable	Coef.	Std. Err.	t
i's unit outgoing price	-0.041	0.725	-0.06
j's unit incoming price	-1.602+	0.852	-1.88
Number of overlapping ties (Lag 1 month)	**31.530**	0.416	75.77
i's age	0.961	1.023	0.94
i's gender (female)	**195.878**	15.404	12.72
i's VIP status_J	**199.971**	21.428	9.33
i's VIP status_Y	**116.523**	14.230	8.19
i's VIP status_Z	31.069	46.481	0.67
Intercept	82.435+	44.162	1.87
R-sq (within)	0.0652		
R-sq (between)	0.0562		
R-sq (overall)	0.0515		
Number of obs	95524		
Number of groups	5475		

Bold: significant at 5% level; +: significant at 10% level
* fixed effects added to receiver *j*

Reference

Alba, R.D. and C. Kadushin (1976), "The Intersection of Social Circles: A New Measure of Social Proximity in Networks," *Social Methods and Research*, 5:77-102.

Blau, Peter (1964), *Exchange and Power in Social Life*. New York: Wiley.

Blattberg, R.C., R. Briesch and E. J. Fox (1995), "How Promotion Work," *Marketing Science*, Vol. 14, G122-132.

Blumstein, Philip and Peter Kollock (1988), "Personal Relationships," *Annual Review of Sociology*, 14, 467-90.

Coslett, S. R. (1981), "Maximum likelihood estimator for choice-based samples," *Econometrica*, 49: 1289–1316.

Granovetter, Mark (1973), "The Strength of Weak Ties," *American Journal of Sociology*, 78: 1360-1380.

Granovetter, Mark (1985), "Economic Action and Social Structure: The Problem of Embeddedness," *American Journal of Sociology*, Vol. 91, No. 3, 481-510.

Guadagni, Peter M. and John D.C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2 (3), 203–238.

Huang, Ching-I (2008), "Estimating Demand for Cellular Phone Service under Nonlinear Pricing," *Quantitative Marketing and Economics*, pp. 1570-7156.

Iacobucci, Dawn (1996), *Networks in Marketing*, Sage Publications, Thousand Oaks, California.

Imbens, G. (1992), "An efficient methods of moments estimator for discrete choice models with choice-based sampling," *Econometrica*, 60: 1187–1214.

Iyengar, R., A. Ansari, S. Gupta (2007), "A Model of Consumer Learning for Service Quality and Usage," *Journal of Marketing Research*, Vol. XLIV, No. 4

Iyengar, R, K. Jedidi, and R. Kohli (2008), "A Conjoint Approach to Multipart Pricing," *Journal of Marketing Research*, pp. 195-210

Jeon, Doh-Shin, Jean-Jacques Laffont, and Jean Tirole (2004), "On the 'Receiver-pays' Principle," *Rand Journal of Economics*, 35 (1), 85-110.

Katona, Zsolt and Miklos Sarvary (2008), "Network Formation and the Structure of the Commercial World Wide Web," *Marketing Science*, Vol. 27, No. 5, pp. 764-778

Kossinets, Gueorgi and Duncan J. Watts (2006), "Empirical Analysis of an Evolving Social Network," *Science*, 311, January 6, 88-90.

Lambrecht, Anja, Katja Seim, Bernd Skiera (2007), "Does Uncertainty Matter? Consumer Behavior under Three-Part Tariffs," *Marketing Science*, Vol. 26, No. 5, September-October 2007, pp. 698-710.

Lambrecht, Anja, Bernd Skiera (2006), "Paying Too Much and Being Happy about It: Existence, Causes, and Consequences of Tariff-choice Biases," *Journal of Marketing Research*, Vol. 43(2), pp. 212-223.

Marsden, Peter and Karen Campbell (1984), “Measuring Tie Strength,” *Social Forces,* 63 (2), 482-501.

Macaulay, Steward (1963), “Non-contractual Relations in Business: A Preliminary Study,” *American Sociological Review*, 28:55-67.

Miravete, Eugenio (2003), “Choosing the Wrong Calling Plan? Ignorance and Learning,” *American Economic Review*, 93, 297-310.

Mitchell, Bridger M. (1978), “Optimal Pricing of Local Telephone Service,” *American Economic Review*, Vol. 68, No. 4, 517-537.

Montgomery, James D. (1996), “The Structure of Social Exchange Networks: A Game Theoretic Reformulation of Blau’s Model,” *Sociological Methodology*, 26: 193-225.

Narayanan, S., P. Chintagunta and E. Miravete (2007), "The Role of Self Selection, Usage Uncertainty and Learning in the Demand for Local Telephone Service", *Quantitative Marketing and Economics*, 5, pp. 1-34.

Shi, Mengze (2003), “Social Network-Based Discriminatory Pricing Strategy,” *Marketing Letters*, pp. 239-256.

Shy, Oz (2001), *The Economics of Network Industries*, Cambridge University, UK.

Sorenson, Olav and Toby E. Stuart (2008), “Bringing the Context Back In: Settings and the Search for Syndicate Partners in Venture Capital Investment Networks." *Administrative Science Quarterly*, 53: 266-94.

Stephen, Andrew T. and Olivier Toubia (2009), “Deriving Value from Social Commerce Networks,” *Journal of Marketing Research*, forthcoming

Van den Bulte, Christophe and Yogesh Joshi (2007), “New Product Diffusion with Influentials and Imitators,” *Marketing Science*, 26 (3), 400-421.

Van den Bulte, Christophe and Stefan Wuyts (2007), *Social network and marketing*, Marketing Science Institute, Cambridge, Massatchusettes.

Wellman, Barry, Renita Wong, David Tindall, and Nancy Nazer (1997), “A Decade of Network Change: Turnover, Persistence and Stability in Personal Communities,” *Social Networks*, 19, 27-50.

Wasserman, Stanley and Katherine Faust (1994), *Social Network Analysis: Methods and Applications*, Cambridge University Press.