Intra-Household Effects on Demand for Telephone Service: Empirical Evidence

Abstract

Knowing the determinants of consumption decisions is important for targeted marketing. This paper proposes a method to study household adoption of network goods. I empirically investigate the factors which affect the interactions among household members in the choice of telephone service using a game-theoretical model to characterize the interactions. The proposed semiparametric maximum likelihood estimator accounts for potential multiple Nash equilibria. I apply the method to study the subscription decisions for cellular phone service in Taiwan. On average, a consumer's probability of subscribing to cellular service rises 13 percentage points when the other household member chooses to subscribe, suggesting the existence of intra-household network effects. Moreover, intra-household effect is heterogeneous among households. It increases in household income, but decreases in the number of children and the age difference in a household.

Keywords consumption externality, multiple Nash equilibria, demand estimation, mobile phone service, network effect, targeted marketing

JEL Classification C35, D12, D13

1 Introduction

Firms can profit from targeted marketing by charging different prices for different consumers. Nonetheless, to implement targeted marketing, they need to know the determinants of consumer demand. For products with network effects, such as cellular phone service, demand depends on a consumer's own characteristics as well as the characteristics of the network. The main focus of this research is to empirically analyze the heterogeneities of consumption network effects within a household. Specifically, I estimate the determinants for *intra-household effect*, which is defined as the change in a consumer's willingness to use the service in response to the choice of other household members. I propose a game-theoretical framework to investigate the interactions between household members for the subscription of cellular phone service. Although studying the adoption of cellular phone seems less important in recent years since the penetration rate is approaching one in most countries, the estimation method can be used to study other network goods as well as the migration to new generation of cellular phone service. Moreover, the empirical findings from the consumption decision of cellular phone service could be applied to marketing other network goods or to evaluating the demand of introducing new network goods to the market.

While network effects are assumed to be homogeneous in most previous researches, this paper attempts to study the heterogeneity of network effect within a household. Many previous works have found the existence of network effect in several industries. For instance, see Farrell and Klemperer (2007) for a survey of empirical studies on network effects. However, network effect is typically assumed to depend only on the number of users in the industry. This simplification implies that the network effect resulting from any other user is identical. Nonetheless, as Rohlfs (1974) pointed out in his seminal article, this simplification assumption is not always true in reality. The structure of a consumer's social network matters. In a recent paper, Hartmann (2010) considers the heterogeneity by assuming that the network effects are unobserved and follow a log-normal distribution. On the contrary, the contribution of my research is to analyze how the network effects vary with observed characteristics.

I use a model of binary subscription decision on cellular phone service to study households with two members. Because a consumer's demand for the service may depend on the choice of the other household member either positively or negatively in theory, finding out the sign and magnitude of the intra-household effect is an empirical issue. For example, consider a household consists of a husband and a wife. There are several possible reasons for *positive* intra-household effect. The first one is *direct network effect*. Because the husband can be contacted by phone more frequently, the wife's demand for cellular phone service increases. The second reason is *indirect network effect*. For instance, since the husband's knowledge of cellular phone service from his own consumption reduces the wife's search cost on her subscription decision, she is likely to have higher demand. A third explanation is *tariff-mediated network effect*. When the price of a cellular-to-cellular phone call is lower than that of a landline-to-cellular phone call[1], the wife can pays less for a call from a cellular phone than one from a landline phone. Consequently, she may have higher demand for cellular phone service. Similarly, if carriers offer family plans which lowers the subscription fee for a second cellular phone, there exists positive intra-household effect on the consumption. On the other hand, intra-household effect may be *negative* if a cellular phone is a *public good* in a household. Then, each household member wants to be a free rider and shares the usage of the other person's cellular phone.

The primary difficulty in estimating models with externalities is to deal with multiple Nash equilibria. Because there is no one-to-one mapping between model primitives and outcomes in the presence of multiple equilibria, we cannot compute the likelihood function for maximum likelihood estimation. Bresnahan and Reiss (1991) suggest to aggregate non-unique outcomes into *observational equivalence classes* and estimate model primitives based on these classes. For example, in Bresnahan and Reiss (1990)'s entry model, the spillover effects between two firms are always negative and the equilibrium number of entrants is unique. Therefore, estimation can be carried out by using the observed number of entrants. Tamer (2003) shows that point identification of model primitives can be achieved and estimated in a two-by-two discrete game despite multiple equilibria. Moreover, the proposed semiparametric estimator has a smaller standard errors than the maximum likelihood estimator based on observational equivalence classes. I generalize his model to allow the interdependence to be heterogeneous across households. Model parameters are pointwise identified in my model as well. Following Tamer (2003)'s framework, estimation is carried out in two steps. The first step uses nonparametric regression to determine the selection among multiple equilibria, and the second step obtains model parameters by maximum likelihood estimation.

I apply the econometric approach to study the demand for cellular phone service in Taiwan. Intra-household effect is positive on average, with a marginal effect of increasing a consumer's probability to subscribe by 13.05 percentage points. This finding suggests the existence of network effect within a household. Furthermore, the strength of intra-household effects is associated with several observed characteristics. My estimation results are consistent with the intuition that intra-household network effect is stronger when household members spend less time together for family life and have stronger

[1] This is the case when cellular carriers offers in-network discounts.

desire to talk to each other on cellular phones. Specifically, the estimated intra-household effect increases in household income and is higher for households in cities, but the effect decreases in the number of children and the age difference between the two members. As a consequence, when firms perform targeted marking to profit from intra-household network effects, they should focus more on those with stronger intra-household effects. Besides, while many previous empirical researches impose Pareto optimality as an equilibrium selection rule, my estimation shows that only 39% of households choose their Pareto optimal outcome when multiple equilibria exist. Therefore, imposing Pareto optimality to estimate games with multiple equilibria could be problematic when the interaction is strong.

In the next section, I briefly summarize related literature. Section 3 introduces the econometric model and its implications for targeted marketing. The estimation method is described in Section 4. Section 5 introduces the data used in the empirical study and the background of the cellular phone service market in Taiwan. Empirical results are presented in Section 6. Concluding remarks are given in the final section.

2 Related Literature

Estimating demand is important for conducting targeted marketing strategies. There is a rich literature on estimating household demand for telecommunication service, but these studies usually ignore social interactions. They generally use household-level survey data. Each household is treated as a single decision-maker in the estimation. Only household heads' individual characteristics are included in the demand estimation.[2] This approach implicitly assumes the demand to be solely determined by household heads. Other members can influence the decision only indirectly through household-level variables. Nonetheless, such an assumption is unlikely to be true in reality. In contrast, each individual is treated as a decision-maker in my model and I consider the interaction within a household. Among many previous studies on cellular phone service demand, Iyengar (2004) and Grzybowski and Pereira (2011) estimated the cellular phone service demand by using data from billing records. No demographic characteristic is observed in Iyengar (2004)'s data while only very few demographic characteristics are available in Grzybowski and Pereira (2011)'s work. Grzybowski (2008) used UK household survey data to estimate switching costs in mobile phone service. He included each consumer's demographic variable, but did not

[2]Some researches used operator-level data to estimate the demand for cellular phone service. Individual demographic variables are not included in the estimation. For example, Doganoglu and Grzybowski (2007) investigated the network effect of penetration rates on the demand for mobile phone service in Germany. Bajari, Fox, and Ryan (2008) estimated demand by using each operator's market share rank. Their focus is the value of national coverage.

consider the interaction among household members.[3]

My research topic is similar to Birke and Swann (2006). They found the existence of network effects among household members in the choice of mobile phone operator in the U.K. However, their estimation procedure does not account for the endogeneity of the other members' choices. In contrast, I deal with the endogeneity by explicitly modeling the interactions among individuals within a household.

As Browning, Bourguignon, Chaippori, and Lechene (1994) pointed out, household behavior depends on intra-household interactions unless we impose some restrictive hypotheses such as transferable utilities. They proposed a collective household model: Household members bargain with each other to allocate their overall resources. Individual consumption depends on the allocation. The bargaining power depends on individual characteristics. The resource allocation must achieve Pareto efficiency in the bargaining process. Using data on couples with no children, they find that the allocation of expenditure depends on the relative incomes and relative ages of the couples, rejecting the hypotheses of a single decision-maker in a household. See Vermeulen (2002) for further discussions on the collective household model. Different from Browning et al. (1994)'s collective household model, the equilibrium allocation is not restricted to be Pareto optimal in my game-theoretical model.

Many recent researches propose methods to estimate games with multiple Nash equilibria in simultaneous-move complete information game. See Berry and Reiss (2007) for a survey on some of them. One approach is to consider the selection rule among these equilibria. For example, Jia (2008) imposed an ad hoc selection rule to choose among multiple market equilibria in the entry game of retailers. In Hartmann (2010)'s study of social interactions, she assumes that players always choose the equilibrium that maximize their total surplus. Bajari, Hong, and Ryan (2010) proposed a simulation-based method to estimate the selection rule. Another approach uses bounds estimation based on inequality constraints derived from necessary conditions for pure strategy Nash equilibria (Chernozhukov, Hong, and Tamer, 2007; Ciliberto and Tamer, 2009; Pakes, Porter, Ho, and Ishii, 2006). My research is an extension of Tamer (2003) on two-by-two complete information games. Equilibrium selection rule is estimated from the data by using a first-step nonparametric regression. I extend Tamer (2003)'s model to allow social interactions to differ in observe characteristics.[4]

[3]In addition to study the demand for cellular phone service, there are also many previous researches on landline phone service using similar approach. For instance, see Train, McFadden, and Ben-Akiva (1987); Train, Ben-Akiva, and Atherton (1989); Rappoport and Taylor (1997); Solvason (1997); Madden and Simpson (1997); Duffy-Deno (2001); Miravete (2002); Rodini, Ward, and Woroch (2003); Economides, Seim, and Viard (2008).

[4]Some research deal with multiple equilibria under an incomplete information game, such as Vitorino (2011). However, because household members are familiar with each other, assuming complete information in the game is more appropriate in the context of my research.

3 Econometric Model

The presence of intra-household effect means that consumption depends on the decision of other household members. In this section, I generalize the static discrete choice model proposed by Bresnahan and Reiss (1991) to allow heterogeneous intra-household effect. Most discussions focus on Nash equilibria under a simultaneous-move non-cooperative game between a household with two members. I will consider other game structures at the end of this section.

3.1 Discrete Choice Model

For household i, there are two members $j \in \{1, 2\}$. All characteristics of each member are observed by both members. *Household-level* characteristics, such as household income, residence location, ..., etc., are common to both member, while *individual-level* characteristics, such as gender, age, education ...etc., are individual-specific. Furthermore, some characteristics, such as the network size of coworkers, are observed only by the two household members, but not by the econometrician.

A consumer's subscription decision depends on both *direct effect* and *intra-household effect*. The former effect is determined by the consumer's own individual-level characteristics as well as the household-level characteristics. The latter effect depends on the choice of the other household member. Its magnitude is normalized to zero when the other member does not subscribe. I assume the intra-household effect is reciprocal between the two members and its magnitude is determined by household-level characteristics.

Let the binary variable $y_{ij} \in \{0, 1\}$ denote *the subscription decision* of individual j in household i. Let $y_{ij} = 1$ if and only if the individual subscribes to the telephone service. The demand is characterized by

$$y_{ij} = 1 \quad \Leftrightarrow \quad \underbrace{[\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}]}_{\text{direct effect}} \quad + \quad \underbrace{y_{i(3-j)}[\mathbf{z}_i'\boldsymbol{\gamma}]}_{\text{intra-household effect}} \quad > 0, \tag{1}$$

where $(3 - j)$ is the index for the other member in the household. The terms in the first bracket of equation (1) represents the direct effect of consumption. The term in the second bracket, $\mathbf{z}_i'\boldsymbol{\gamma}$, captures the magnitude of the intra-household effect. The vector $\mathbf{x}_{ij}$ is member j's *observed characteristics* (including a constant term and both household-level and individual-level characteristics) and the scalar ε_{ij} represents his *unobserved individual characteristic* that is independent of observed characteristics. The vector $\mathbf{z}_i$, which includes a constant term and all *household-level characteristics*, determines the magnitude of intra-household effect. To identify the model parameters, at least one of the elements in the vector $\mathbf{x}_{ij}$ (such as member j's age) is not a household-level characteristic. My model reduces to the standard probit model if the intra-household effect vanishes ($\boldsymbol{\gamma} = \mathbf{0}$). If the intra-household effect is restricted to be constant across households, as in Tamer (2003)'s model, the vector $\mathbf{z}_i$ only contains the constant term ($\mathbf{z}_i'\boldsymbol{\gamma} \equiv \gamma_0$).

The unobserved characteristics ($\varepsilon_{i1}, \varepsilon_{i2}$) are assumed to be jointly normally distributed, independently across households, and independent of observed characteristics ($\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i$).

$$\begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right). \tag{2}$$

The variance of ε_{ij} is normalized to one. The correlation coefficient ρ in (2) is to be estimated.[5]

Finally, let $Y_i = y_{i1} + y_{i2}$ denote the total number of subscribers in the household.

3.2 Nash Equilibria

Consider a simultaneous-move non-cooperative game. When there is positive intra-household effect ($\mathbf{z}_i'\boldsymbol{\gamma} > 0$), there are multiple Nash equilibria when ($\varepsilon_{i1}, \varepsilon_{i2}$) lies in the region $(-\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_{i1}'\boldsymbol{\beta}) \times (-\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_{i2}'\boldsymbol{\beta})$.[6] Both $(y_{i1}, y_{i2}) = (0,0)$ and $(y_{i1}, y_{i2}) = (1,1)$ are equilibria when $(\varepsilon_{i1}, \varepsilon_{i2})$ is in this region. Given the observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$, the model predicts exact probability for $(y_{i1}, y_{i2}) = (0,1)$ and $(y_{i1}, y_{i2}) = (1,0)$. In contrast, the model can only give bounds for the probability of the event $(y_{i1}, y_{i2}) = (0,0)$ because we cannot know which one is the realized outcome when multiple equilibria occur. The lower and upper bounds for the probability of $(y_{i1}, y_{i2}) = (0,0)$ is

$$\Pr\left(\{\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta}\} \cup \{\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}\} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i\right)$$

and

$$\Pr(\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i).$$

respectively. Similarly, we only know the bounds for the probability of $(y_{i1}, y_{i2}) = (1,1)$.

When the intra-household effect is negative ($\mathbf{z}_i'\boldsymbol{\gamma} < 0$), there are multiple equilibria of $(0,1)$ and $(1,0)$ if $(\varepsilon_{i1}, \varepsilon_{i2})$ lies in the region $(-\mathbf{x}_{i1}'\boldsymbol{\beta}, -\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}) \times (-\mathbf{x}_{i2}'\boldsymbol{\beta}, -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma})$.[7] The model gives the exact

[5] The discrete choice (1) focuses on the interactions between household members. This specification does not rule out potential network effects from other individuals, such as friends, coworkers, employers, etc. These effects are captured by ε_{ij}.

[6] See Figure 2 in Bresnahan and Reiss (1991) for a graphic illustration.

[7] See Figure 1 in Bresnahan and Reiss (1991) for a graphic illustration.

probabilities of $(y_{i1}, y_{i2}) = (0,0)$ and $(y_{i1}, y_{i2}) = (1,1)$, but not $(y_{i1}, y_{i2}) = (0,1)$ and $(y_{i1}, y_{i2}) = (1,0)$.

Regardless the sign of intra-household effect, the probability of observing exactly one subscriber in a household ($Y_i = y_{i1} + y_{i2} = 1$) for given observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ can be written as

$$\begin{aligned} & P_1(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho) \\ \equiv & \Pr(Y_i = 1 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}) \\ = & \Pr(\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}, \varepsilon_{i2} > -\mathbf{x}_{i2}'\boldsymbol{\beta} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i) + \Pr(\varepsilon_{i1} > -\mathbf{x}_{i1}'\boldsymbol{\beta}, \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i) \\ & - \mathbf{1}\{\mathbf{z}_i'\boldsymbol{\gamma} < 0\} \Pr(-\mathbf{x}_{i1}'\boldsymbol{\beta} < \varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_{i2}'\boldsymbol{\beta} < \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i), \end{aligned} \tag{3}$$

where $\mathbf{1}\{\cdot\}$ denotes the indicator function.

However, the exact probabilities of no subscriber ($Y_i = 0$) and two subscribers ($Y_i = 2$) in a household are unknown when intra-household effect is positive because we do not know how individuals choose among multiple Nash equilibria.[8] Without loss of generality, we only need to focus on the probability $\Pr(Y_i = 0 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ because $\Pr(Y_i = 2 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ can be obtained from $1 - \Pr(Y_i = 0 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i) - \Pr(Y_i = 1 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$. Without imposing any equilibrium selection rule, the probability of no subscriber in a household is bounded by an interval. The upper bound occurs when individuals always fail to coordinate their decisions in the event of multiple Nash equilibria.

$$P_0^U(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho) \equiv \Pr(\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i). \tag{4}$$

The lower bound is achieved when individuals can perfectly coordinate.

$$\begin{aligned} P_0^L(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho) \equiv & \Pr(\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i) \\ & - \mathbf{1}\{\mathbf{z}_i'\boldsymbol{\gamma} > 0\} \Pr(-\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma} < \varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta}, -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma} < \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i). \end{aligned} \tag{5}$$

[8] Contrary to my model, in Bresnahan and Reiss (1990)'s entry model, the effect must be negative. As a result, the value of Y_i is unique determined in equilibrium.

3.3 Evaluating the Intra-Household Effect

The intra-household effect for an individual is the decision change resulted from the other household member's subscription decision. For individual i in household j, the effect is

$$\mathbf{1}\{[\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] + [\mathbf{z}_i'\boldsymbol{\gamma}] > 0\} - \mathbf{1}\{[\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] > 0\} \tag{6}$$

Since we do not observe ε_{ij}, the *marginal intra-household effect* is defined as the expected value of the above expression conditional on observed characteristics $(\mathbf{x}_{ij}, \mathbf{z}_i)$.[9] It is easy to show that the marginal effect can be expressed as the change in the subscription probability conditional on observed characteristics when the other member switches the subscription decision.

$$\begin{aligned} &E\left[\mathbf{1}\{[\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] + [\mathbf{z}_i'\boldsymbol{\gamma}] > 0\} - \mathbf{1}\{[\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] > 0\} \middle| \mathbf{x}_{ij}, \mathbf{z}_i\right] \\ &= \Pr\left([\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] + [\mathbf{z}_i'\boldsymbol{\gamma}] > 0 | \mathbf{x}_{ij}, \mathbf{z}_i\right) \; - \; \Pr\left([\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] > 0 | \mathbf{x}_{ij}, \mathbf{z}_i\right). \end{aligned} \tag{7}$$

3.4 Implications for Targeted Marketing

Firms can use targeted marketing to implement price discrimination and increase profits. Since demand varies with a consumer's observed characteristics, firm can conduct targeted marketing based on these characteristics. Moreover, the interdependence within a household implies that targeted marketing needs to account for other household members' characteristics as well. The discrete choice model (1) implies that consumers with a lower value of the direct effect $\mathbf{x}_{ij}'\boldsymbol{\beta}$ have lower demand and firms should offer more discounts for these consumers. Furthermore, when the intra-household effect $\mathbf{z}_{ij}'\boldsymbol{\gamma}$ is positive, there exists positive externality between the choices of the two household members. As a result, if one household member, say $j = 1$, has a lower value of the direct effect $\mathbf{x}_{i1}'\boldsymbol{\beta}$, the other member is also less likely to subscribe. Hence, firms should also offer more discounts to the other household member. The magnitude of the intra-household effect $\mathbf{z}_{ij}'\boldsymbol{\gamma}$ indicates the strength of the effect of member 1's characteristics $\mathbf{x}_{i1}$ on member 2's subscriptions.

[9] The definition is analog to the marginal effect of a binary explanatory variable in a standard probit model.

3.5 Alternative Game Structures

In this subsection, I discuss two alternative game structures: a simultaneous-move cooperative game and a sequential-move game.

First, suppose that household members can perfectly coordinate their consumption decisions as in a simultaneous-move cooperative game. Different from a noncooperative game, the equilibrium number of subscribers in a household must be unique. This is because both individuals can fully coordinate to increase their total surplus. As a result, both would choose to subscribe to cellular phone service if $\mathbf{z}'_{ij}\boldsymbol{\gamma} > 0$ and $(\varepsilon_{i1}, \varepsilon_{i2})$ lies in the region of multiple Nash equilibria in a non-cooperative game.

Secondly, suppose that the two individuals in a household make their subscription decisions sequentially. It is straightforward to derive the subgame-perfect Nash equilibrium by backward induction. The equilibrium number of subscribers is also unique. When both zero and two subscribers are Nash equilibria in a simultaneous-move noncooperative game, the first mover would choose to subscribe in a sequential-move game because he/she expects the second mover to subscribe.

In summary, the equilibrium number of subscribers is the same under the two alternative game structures. Moreover, these two game structures can be viewed as imposing an equilibrium selection rule on the Nash equilibria of a simultaneous-move noncooperative game: "Whenever multiple Nash equilibria exist, both individuals choose to subscribe." As a consequence, the estimation based on the simultaneous-move noncooperative game is the most robust among these game structures.

4 Estimation Approach

This section considers the identification of the discrete choice model (1). I then present a semiparametric maximum likelihood estimator and conduct Monte Carlo experiments to demonstrate the performance of the estimator.

4.1 Identification

Although multiple Nash equilibria are possible, the parameters in the econometric model are pointwise identified. My model is similar to but more complicated than Tamer (2003). Tamer's model is identified when we have data on the individual decisions (y_{i1}, y_{i2}). However, the data set that I use only reports the aggregate decision in a household $(Y_i = y_{i1} + y_{i2})$, not individual choices. Moreover, instead of assuming a constant value, I allow the interaction to vary on observed household characteristics. Nonetheless, the following theorem shows that all parameters are pointwise identified. I relegate the proof to Appendix A.

Theorem 1. *Suppose that there exists a regressor of individual characteristics* (x_{i1k}, x_{i2k}) *with* $x_{i1k}, x_{i2k} \notin \mathbf{z}_i$ *and* $\beta_k \neq 0$ *and such that the conditional distribution of* $x_{i1k}|x_{-i1k}$ *has an everywhere positive Lebesgue density where* $\mathbf{x}_{-i1k} \equiv (x_{i11}, \ldots, x_{i1,k-1}, x_{i1,k+1}, \ldots, x_{i1K})'$*. Then the parameters,* $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$*, are identified if the matrices* $X_1 \equiv [\mathbf{x}_{11}\ \mathbf{x}_{21} \cdots \mathbf{x}_{N1}]$*,* $X_2 \equiv [\mathbf{x}_{12}\ \mathbf{x}_{22} \cdots \mathbf{x}_{N2}]$*, and* $Z \equiv [\mathbf{z}_1\ \mathbf{z}_2 \cdots \mathbf{z}_N]$ *have full rank.*

4.2 Semiparametric Maximum Likelihood Estimator

If intra-household effect is negative, I know the exact probability of the events $\{Y_i = 0\}$, $\{Y_i = 1\}$, and $\{Y_i = 2\}$ conditional on the observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$. Consequently, the usual likelihood can be computed. On the contrary, the exact probabilities of $\{Y_i = 0\}$ and $\{Y_i = 2\}$ are unknown when the effect is positive. I use a semiparametric maximum likelihood estimator, as suggested by Tamer (2003), to obtain the parameters in the demand model. The estimation consists of two steps. The first step uses a kernel regression to obtain the empirical probability of $\{Y_i = 0\}$ conditional on the observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$. The second step replaces the unknown probabilities in the likelihood function by the empirical probabilities obtained in the first step and maximizes the likelihood to obtain the parameter estimates.

Define the conditional probability of the event $\{Y_i = 0\}$ for observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ as

$$H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i) = \Pr\left(Y_i = 0 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i\right).$$

When the function H is known, I can write down the likelihood, and the parameters $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$ are estimated by maximizing the logarithm of the likelihood function. For a random sample with size N,[10] the logarithm

[10] The survey data I use to perform estimation is not a random sample. Therefore, I need to adjust for the sampling weights in my calculation. To ease the exposition, however, I present the estimator without writing down the sampling weights.

of the likelihood function is

$$
\begin{aligned}
L(\boldsymbol{\beta},\boldsymbol{\gamma},\rho;H)=\frac{1}{N}\sum_i\Big\{&\mathbf{1}[Y_i=0]\log(H(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i))\\
&+\mathbf{1}[Y_i=1]\log\left(P_1\left(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\boldsymbol{\gamma},\rho\right)\right)\\
&+\mathbf{1}[Y_i=2]\log\Big(1-H(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)-P_1\left(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\boldsymbol{\gamma},\rho\right)\Big)\Big\} \qquad (8)
\end{aligned}
$$

The unknown function $H(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$ represents the probability of observing no subscriber in a household. When multiple Nash equilibria exist, We know $H(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$ is bounded by the interval $[P_0^L(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\boldsymbol{\gamma},\rho),P_0^U(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\boldsymbol{\gamma},\rho)]$, where P_0^L and P_0^U are defined in equations (4) and (5), but the model cannot predict the exact probability. I follow Tamer (2003)'s suggestion to approximate the unknown function by a kernel regression of the event $\{Y_i=0\}$ on the observed characteristics $(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$.

Any function which locally approximates the true probability of $\{Y_i=0\}$ can be used in the estimation. Suppose that the conditional probability $H(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$ is a continuous function. Then I can use the following Gaussian kernel regression to estimate it.

$$
\hat{H}(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)=\frac{\frac{1}{N}\sum_{i'}\mathbf{1}[Y_{i'}=0]\phi\left(\frac{1}{B}d[(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i),(\mathbf{x}_{i'1},\mathbf{x}_{i'2},\mathbf{z}_{i'})]\right)}{\frac{1}{N}\sum_{i'}\phi\left(\frac{1}{B}d[(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i),(\mathbf{x}_{i'1},\mathbf{x}_{i'2},\mathbf{z}_{i'})]\right)}, \qquad (9)
$$

where ϕ is the density function of a standard normal distribution, B is a fixed bandwidth, and the metric d is defined as the Euclidean distance normalized by the standard deviation of each variable,

$$
d[(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i),(\mathbf{x}_{i'1},\mathbf{x}_{i'2},\mathbf{z}_{i'})]\equiv\sqrt{\frac{1}{2K+L}\left[\sum_{j=1}^{2}\sum_{k=1}^{K}\frac{(x_{ijk}-x_{i'jk})^2}{Var(x_{\cdot jk})}+\sum_{l=1}^{L}\frac{(z_{il}-z_{i'l})^2}{Var(z_{\cdot l})}\right]},
$$

where K and L are the lengths of the covariate vectors $\mathbf{x}_{ij}$ and $\mathbf{z}_i$, respectively. I use the Scott's rule to select the bandwidth B (Scott, 1992), but I also consider alternative choices of the bandwidth for robustness check in Appendix B.

At the true parameter value, the conditional probability function $H(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$ is bounded by the interval $[P_0^L(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\boldsymbol{\gamma},\rho),P_0^U(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\boldsymbol{\gamma},\rho)]$. Therefore, I truncate the kernel regression estimator $\hat{H}(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$ by the upper and lower bounds and denote the truncated function as $\hat{\hat{H}}(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\boldsymbol{\gamma},\rho)$. Replacing H in the likelihood (8) by the consistent estimator $\hat{\hat{H}}$, I can consistently estimate $(\boldsymbol{\beta},\boldsymbol{\gamma},\rho)$ by maximizing $L(\boldsymbol{\beta},\boldsymbol{\gamma},\rho;\hat{\hat{H}})$.

The two-step procedure is implemented as the following. In the first step, I run the kernel regression of the event $\{Y_i = 0\}$ on observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ to obtain $\hat{H}$ as defined in (9). In the second step, I search over the parameter space to solve the nonlinear optimization problem $\max_{\boldsymbol{\beta},\boldsymbol{\gamma},\rho} L(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho; \hat{\hat{H}})$. For any given parameter $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$ in optimization search, I compute the upper and lower probability bounds P_0^L and P_0^U for the event $\{Y = 0\}$ at the given parameter value to obtain the truncated probability function $\hat{\hat{H}}$, and then plug it into the objective function $L(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho; \hat{\hat{H}})$.

To obtain the variance of the estimator $(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}}, \hat{\rho})$, I need to account for the standard errors resulting from the kernel regression in the first step. It is complicated to analytically compute the variance. As a result, I calculate the variance by the bootstrap method. Specifically, I resample households from the original data. For each resampled data, I obtain a two-step estimator for $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$ as proposed above. The variance of the estimator $(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}}, \hat{\rho})$ is then obtained from the empirical distribution of the estimators computed using each of the resampled data.

4.3 Monte Carlo Simulations

To demonstrate the performance of the semiparametric estimator proposed in the previous subsection, I conduct Monte Carlo experiments using the discrete choice model (1). For individual j in household i, the direct effect is determined by one household-level variable x_{ij1} and one individual-level variable x_{ij2}, and the intra-household effect is determined by a household-level observed variable z_i. Specifically, the choice model (1) can be expresses as

$$y_{ij} = 1 \quad \Leftrightarrow \quad [\beta_0 + \beta_1 x_{ij1} + \beta_2 x_{ij2} + \varepsilon_{ij}] + y_{i(3-j)}[\gamma_0 + \gamma_1 z_i] > 0. \tag{10}$$

The observed variables $(x_{i11}, x_{i12}, x_{i22}, z_i)$ in each household[11] are generated from the standard normal distribution $N(0, 1)$ independently across i. The unobserved characteristics $(\varepsilon_{i1}, \varepsilon_{i2})$ are drawn from a joint normal distribution with unit variance and correlation coefficient ρ.

I perform the Monte Carlo experiments with various true parameters as well as different estimation specifications. Table 1 summarizes the results. Each column shows the mean and standard deviation computed from 100 simulated samples. Each sample consists of 3,500 household in Column (A) – (F). This sample size is chosen because it is close to the sample size in my empirical study, which has 3,489 households.

[11] Note that $x_{i11} = x_{i21}$ because they represent the same household-level variable.

Table 1: Monte Carlo Results

Specifications	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
Estimated Parameters								
β_0	**-2.000**	**-2.000**	**-2.000**	**-2.000**	**-2.000**	**-2.000**	**-2.000**	**-2.000**
	-1.990	-1.934	-1.662	-1.970	-2.004	-1.985	-2.097	-1.993
	(0.065)	(0.095)	(0.176)	(0.068)	(0.066)	(0.065)	(0.199)	(0.147)
β_1	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**
	3.076	3.236	3.332	3.091	3.049	3.078	3.078	3.087
	(0.093)	(0.102)	(0.162)	(0.103)	(0.094)	(0.093)	(0.341)	(0.194)
β_2	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**
	3.061	3.153	3.189	3.065	3.048	3.061	3.128	3.067
	(0.093)	(0.111)	(0.166)	(0.104)	(0.095)	(0.094)	(0.311)	(0.187)
γ_0	**1.000**	**3.000**	**8.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	0.973	2.947	7.918	0.936	1.016	0.965	1.259	0.969
	(0.092)	(0.159)	(0.458)	(0.084)	(0.092)	(0.092)	(0.233)	(0.187)
γ_1	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	1.017	1.037	1.058	1.038	1.025	1.016	1.093	1.023
	(0.060)	(0.053)	(0.108)	(0.064)	(0.062)	(0.060)	(0.187)	(0.107)
ρ	**0.000**	**0.000**	**0.000**	**-0.500**	**0.000**	**0.000**	**0.000**	**0.000**
	-0.037	0.035	0.291	-0.471	-0.087	-0.029	-0.765	-0.032
	(0.156)	(0.158)	(0.248)	(0.112)	(0.154)	(0.157)	(0.481)	(0.322)
Estimated Marginal Intra-Household Effect								
Mean	**0.088**	**0.265**	**0.587**	**0.088**	**0.088**	**0.088**	**0.088**	**0.088**
	0.084	0.247	0.540	0.081	0.089	0.084	0.109	0.085
	(0.008)	(0.010)	(0.013)	(0.007)	(0.008)	(0.008)	(0.024)	(0.016)
Standard Deviation	**0.186**	**0.323**	**0.419**	**0.186**	**0.186**	**0.186**	**0.186**	**0.186**
	0.184	0.316	0.428	0.184	0.188	0.184	0.209	0.185
	(0.009)	(0.008)	(0.003)	(0.008)	(0.009)	(0.009)	(0.020)	(0.016)
Pr(Multi. Nash Equil.)	0.017	0.077	0.338	0.016	0.018	0.017	0.023	0.017
Pr($\hat{H}$ Right-Truncated)	0.488	0.475	0.431	0.493	0.481	0.489	0.485	0.489
Pr($\hat{H}$ Left-Truncated)	0.490	0.422	0.151	0.488	0.487	0.492	0.489	0.491
Household Size	3500	3500	3500	3500	3500	3500	500	1000
Bandwidth in Kernel Regression	0.343 (Scott)	0.343 (Scott)	0.343 (Scott)	0.343 (Scott)	0.2	0.5	0.437 (Scott)	0.401 (Scott)

Notes: True values are in boldface. Mean of estimates are shown below true values. Standard deviations of estimates are in parentheses. Each Monte Carlo simulation is conducted for 100 samples.

Column (A) is the benchmark case. True parameters are $\beta_0 = -2.0$, $\beta_1 = 3.0$, $\beta_2 = 3.0$, $\gamma_0 = 1.0$, $\gamma_1 = 1.0$, and $\rho = 0$. When multiple Nash equilibria (i.e. both $Y_i = 0$ and $Y_i = 2$ are equilibria.) exist, I assume that the event $Y_i = 2$ occurs randomly with probability 0.7. By choosing $\gamma_0 = 1.0$, the probability of multiple Nash equilibria is merely 1.7%. This percentage is close to the empirical finding in Section 6. As is shown in the table, all the parameters can be estimated reasonably well. Besides, both the mean and the standard deviation of the marginal intra-household effect are close to the true values.[12]

Columns (B) and (C) increases the parameter of γ_0 to 3.0 and 8.0, respectively. As this parameter increases, intra-household effect becomes stronger and the probability of multiple equilibria is higher. The semiparametric estimator can still reasonably estimate the true parameters. Nonetheless, it appears the mean of marginal intra-household effects to be somewhat underestimated when the probability of multiple Nash equilibria increases to 33.8% in Column (C).

The correlation coefficient of the unobserved characteristics $(\varepsilon_{i1}, \varepsilon_{i2})$, ρ, is not accurately estimated since it has a larger standard deviation across these specifications. Column (D) changes the correlation coefficient from 0 in Column (A) to -0.5. The estimated values of parameters other than ρ are very similar to those in Column (A).

The bandwidth used in the kernel regression affects the estimated value of $\hat{H}$. Columns (A) – (D) are based on the Scott's rule. I try different bandwidths in Columns (E) and (F). The estimated results are not sensitive to the choice of the bandwidth. In fact, since the probability of multiple equilibria is less than 2%, it is not surprising that the estimation is robust to the bandwidth choice.

I reduce the sample size from 3,500 households to 500 in Column (G) and 1,000 in Column (H). Unsurprisingly, when the sample size is smaller, there are more biases in the estimates and the standard deviations are also larger. Nonetheless, the biases are generally less than one standard deviation.

4.4 Estimation under Alternative Game Structures

As discussed in Subsection 3.5, the equilibrium number of subscribers in a household is the same for a simultaneous-move cooperative game and for a sequential-move game. For these two game structures, the number of subscribers is unique in equilibrium. Since there is a one-to-one mapping between the model primitives and the observed outcome, the model coefficients can be estimated by the usual maximum likelihood estimation.

[12] The percentage of truncation appears to be large in a first glance. However, this is not surprising because the difference between P_0^L and P_0^U (i.e. the probability of multiple Nash equilibria) is very small. Hence, only a small proportion of $\hat{H}$ lies in the interval $[P_0^L, P_0^U]$.

Note that, although the proposed two-step estimator is based on a simultaneous-move noncooperative game, it remains a consistent estimator under the two alternative game structures. Because the probability of observing no subscriber in a household is $P_0^L(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ for the two alternative game structures, the kernel estimator $H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ in the first step should converge to $P_0^L(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ in probability if the data generating process follows these two alternative game structures. Therefore, using the proposed two-step estimator is robust to different game structures.

5 Data

The data come from the 2003 Survey of Family Income and Expenditure in Taiwan. This survey was conducted by the Directorate-General of Budget, Accounting and Statistics in early 2004. It adopts a stratified two-stage sampling method with counties and cities as subpopulations. The universal sampling rate is 0.20%, which is 13,681 households. Because young children are unlikely to make their own decisions and they are unlikely to use telephones, young children are not counted as household members in my empirical work. In this study, only people older than 6 are counted as a household member. The estimation results do not change much by using different age criteria.

Descriptive statistics are presented in Table 2. The first two columns are means and standard deviations for the subsample with two household members. The final two columns are for the entire sample in the survey. The upper panel shows the household-level variables, while the lower panel presents individual-level variables. Based on the age criterion define in the previous paragraph, there are 3,489 households with two members. I use this subsample for the empirical analysis.

The dependent variable Y_i in the empirical study is the number of persons who use the cellular phone service, but I do not observe this variable directly. Table 3 shows the distribution of the number of cellular phones in two-member households. When there is no cellular phone in a household, obviously neither member subscribes to the phone service, $Y_i = 0$. When there is one, only one member in the household chooses to subscribe, $Y_i = 1$. When there is more than one phone, I assume that both individuals choose to have one, $Y_i = 2$. Since each outcome $Y = 0, 1, 2$ is observed in roughly one-third of households, I expect the model parameters to be better estimated by using the 2003 data than using data from more recent years which have much higher penetration rate.

Both household income and individual income are included as explanatory variables.[13] Incomes

[13]Household income is more than twice of individual income in the subsample because part of the household income

Table 2: Descriptive Statistics

	Subsample		Entire Sample		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Description
Household-level Variables					
Cellular Phone	1.071	0.876	1.859	1.324	Number of cell phones
Household Income	0.789	0.603	1.065	0.740	Annual income (million TWD)
City	0.793	0.405	0.807	0.395	Living in a city
Town	0.168	0.374	0.163	0.369	Living in a town
Rural	0.039	0.193	0.030	0.171	Living in rural area
North	0.444	0.497	0.472	0.499	Living in North region
Central	0.223	0.416	0.228	0.419	Living in Cental region
South	0.333	0.471	0.300	0.458	Living in South region
Number of Children	0.270	0.597	0.217	0.530	Number of children younger than 6
Household Size	2.000	0.000	3.310	1.490	Number of HH members
Age Difference	0.107	0.122			Age difference (100 years)
Education Differ.	0.305	0.330			Education difference (10 years)
Income Difference	0.502	0.483			Individual income difference
Individual-level Variables					
Gender	0.511	0.500	0.501	0.500	Female = 1
Age	0.523	0.185	0.387	0.202	Age (100 years)
Education	0.884	0.478	0.963	0.424	Years of Education (10 years)
Employment	0.478	0.500	0.466	0.499	Employed = 1
Individual Income	0.368	0.463	0.301	0.449	Annual Income (million TWD)
sample size	3489		13681		

Notes: The sampling weights are used to compute means and standard deviations.

Table 3: Distribution of the Number of Cellular Phones in a Household

Number of Cellular Phones	Percentage
0	30.57
1	35.32
2	31.32
3	2.02
4	0.73
5	0.05

Notes: Percentages are computed according to the sampling weights.

are measured in Taiwan dollars (TWD). The average exchange rate between US dollars and Taiwan dollars in 2003 is 1 USD = 34.42 TWD. In addition, observed characteristics include geographic variables (region dummies and urban dummies)[14] and demographic variables (gender, age, education, employment, number of children). Researches based on the collective household model find that consumption outcome may depend on relative income and relative age within a household (Browning et al., 1994). Moreover, difference of individual characteristics might affect the desire to talk to each other over phones. For example, couples with similar characteristics probably have more common interest and have stronger interaction on their subscription decisions. Consequently, I construct three household-level variables (*age difference*, *education difference*, and *income difference*) from the original data by computing the difference of individual-level variables in each two-member household.

Although prices of using cellular phone service are important in the subscription decision, prices are not included as an explanatory variable in the estimation. The main reason is that people living in the same region face the same choice set of price menus. The regional dummies control for the price differences across regions. There are four national carriers and two regional carriers in Taiwan in 2003. Each carrier offers a menu of several rate plans. Consumers self-select a rate plan to subscribe to. Each rate plan is available to every consumer in the carrier's operational region. No targeted marketing is observed. No carrier offers family plans which provide discounts for subscribing to more than one phone number simultaneously. Nonetheless, it is common to offer discount rates for intra-network phone calls. Hence, tariff-mediated network effects may exist in this market. See Huang (2008) for a summary of the cellular phone service market in Taiwan in the early 2000s.

Usage of landline phone service may have a strong effect on the choice of cellular phone service. The survey data show that only 1.88% households have no landline phones, 86.56% households own one landline phone, and 11.56% have more than one. Because there is not much variation in this variable, the number of landline phones in a household is excluded as a regressor as well.

cannot be attributed to either member.

[14]As defined by the Directorate General of Telecommunications, the counties and cities included in each of the three regions are the following. (1) North: Keelung, Taipei, Taoyuan, Hsinchu, Yilan, Hualien, and Lienchiang; (2) Central: Miaoli, Taichung, Changhua, Nantou, and Yunlin; (3) South: Chiayi , Tainan, Kaohsiung, Pingtung, Taitung, Penghu, and Kinmen.

6 Empirical Results

This section presents the estimated model parameters and shows the estimated intra-household effects. I also compare the estimation results under alternative game structures.

6.1 Parameter Estimates

I apply the estimation method to analyze the demand for cellular phone service in Taiwan. Table 4 shows the estimated coefficients under various specifications.[15] The goodness-of-fit of these estimation specifications are displayed in Table 5. Each of the specifications can correctly predict the outcome Y for roughly 65% of the observations.

Column (A) is the benchmark case with no intra-household effect. The model is identical to the standard probit model except that unobserved characteristics ε_{ij} are allowed to be correlated within a household. The estimated coefficients for household income and individual income are both significantly positive, suggesting cellular phone service is a normal good. Moreover, age has a negative effect on demand while education and employment have positive effects.

In Column (B), I include intra-household effect in the choice model but restrict the effect to be a constant γ_0 across households. The intra-household effect is significantly positive and has a marginal effect of 10.2 percentage points. Therefore, I can easily reject the hypothesis $\gamma_0 = 0$ by the Wald test. This result suggests the subscription decisions are strategically complements within a household. There exists within-household networks effect on the consumption of cellular phone service.

In the last two columns of Table 4, I allow intra-household effects to be heterogeneous across households. The effect is captured by $\mathbf{z}_i'\boldsymbol{\gamma}$. Column (C) includes all the observed household-level characteristics listed in Table 2 into the vector $\mathbf{z}_i$. In addition, I construct three additional household-level characteristics by averaging individual-level variables within a household: *average age*, *average education years*, and *average employment status*. Column (D) removes the covariates which are estimated to be close to zero in (C). According to likelihood-ratio tests, there is significant improvement in the likelihood from Column (B) to (C), but no significant difference between (C) and (D) at the 5% significance level. Consequently, I select Column (D) as the preferred specification and focus on this specification to discuss the

[15]The unobserved characteristic ε_{ij} in the discrete choice model (1) is defined as characteristic that is independent of observed characteristics. Therefore, the precise interpretation of an estimated coefficient for an observed variable should include the effect from unobserved factors which are correlated with this variable. For example, suppose the attitude toward new technology is correlated with age. The estimated coefficient for age captures both the effect from age per se and from the attitude toward new technology. For the purpose of targeted marketing, it is enough to know this coefficient, regardless the effect coming from age per se or from other factors.

Table 4: Estimated Coefficients

	(A)	(B)		(C)		(D)	
Characteristics	$\boldsymbol{\beta}$	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$
constant	0.237 (0.186)	0.043 (0.153)	0.379*** (0.118) [0.102]	0.085 (0.211)	0.508* (0.299)	0.032 (0.151)	0.527*** (0.119)
Household Income	0.305*** (0.092) [0.077]	0.210*** (0.081) [0.056]		0.118 (0.170) [0.031]	0.092 (0.132) [0.025]		0.179** (0.071) [0.048]
Town	-0.129** (0.060) [-0.033]	-0.120** (0.058) [-0.032]		-0.036 (0.062) [-0.010]	-0.174* (0.095) [-0.047]		-0.221*** (0.057) [-0.060]
Rural	-0.139* (0.077) [-0.035]	-0.130* (0.076) [-0.035]		-0.041 (0.113) [-0.011]	-0.168 (0.135) [-0.045]		-0.226** (0.100) [-0.061]
Central	-0.003 (0.060) [-0.001]	-0.007 (0.054) [-0.002]		0.030 (0.056) [0.008]	-0.052 (0.073) [-0.014]		
South	-0.084* (0.046) [-0.021]	-0.079* (0.042) [-0.021]		-0.058 (0.055) [-0.016]	-0.009 (0.074) [-0.002]		
Number of Children	-0.029 (0.043) [-0.007]	-0.036 (0.037) [-0.010]		0.041 (0.055) [0.011]	-0.173*** (0.053) [-0.047]		-0.129*** (0.043) [-0.035]
Average Age					-0.046 (0.274) [-0.013]		
Average Education					0.092 (0.112) [0.024]		
Average Employment					0.002 (0.093) [0.000]		
Age Difference					-0.946*** (0.253) [-0.255]		-0.862*** (0.214) [-0.232]
Education Difference					0.047 (0.061) [0.013]		
Income Difference					-0.030 (0.164) [-0.008]		
Gender	0.009 (0.087) [0.002]	-0.029 (0.083) [-0.008]		-0.025 (0.084) [-0.007]			
Age	-2.679*** (0.200) [-0.676]	-2.365*** (0.179) [-0.631]		-2.393*** (0.224) [-0.646]		-2.367*** (0.185) [-0.642]	
Education	0.741*** (0.072) [0.187]	0.640*** (0.082) [0.171]		0.570*** (0.081) [0.154]		0.620*** (0.076) [0.168]	
Employment	0.421*** (0.085) [0.114]	0.409*** (0.071) [0.118]		0.340*** (0.074) [0.098]		0.326*** (0.061) [0.094]	
Individual Income	0.617*** (0.215) [0.156]	0.701*** (0.179) [0.187]		0.862*** (0.260) [0.234]		0.995*** (0.140) [0.270]	
ρ	0.013 (0.048)	-0.415*** (0.133)		-0.477*** (0.087)		-0.510*** (0.091)	
Log-Likelihood	-2548.815	-2542.453		-2525.965		-2527.322	

Notes: Standard errors, computed from 50 bootstrap draws, are given in parentheses. Marginal effects, computed as average derivatives of the subscription probability except for for dummy variables whose effects are evaluated for a move from 0 to 1, are in square brackets. Superscripts ***, **, and *represent significance at 1%, 5%, and 10%, respectively. The sample size is 3489 households. Bandwidths are based on Scott's rule.

Table 5: Percentage of Correct Prediction under the Estimated Coefficients

	(A)	(B)	(C)	(D)
$Y = 0$	73.16%	73.72%	73.79%	72.19%
$Y = 1$	48.26%	45.68%	48.85%	49.03%
$Y = 2$	73.92%	74.86%	74.11%	74.72%
Overall	64.62%	64.20%	65.09%	64.87%

Table 6: Summary Statistics for the Estimated Marginal Intra-Household Effects

	(B)	(C)	(D)
Mean of Marginal Intra-Household Effect	10.21%	11.72%	13.05%
	(3.31%)	(2.87%)	(2.37%)
Standard Deviation of Marginal Intra-Household Effect	3.90%	6.27%	6.73%
	(1.14%)	(1.20%)	(0.73%)
Percentage of Positive Marginal Intra-Household Effect	100.00%	99.05%	99.49%
	(0.00%)	(1.74%)	(1.39%)

Notes: Standard errors, computed from 50 bootstrap draws, are given in parentheses. There are two individuals in each of the 3489 households.

intra-household effects in the following subsections.

Based on the estimated coefficients, the probability of multiple Nash equilibria in the number of subscribers is merely 1.68%. As a result, the choice of the bandwidth in the first-step kernel regression has only little effect on the estimation result. In Appendix B, I compare the choice of different bandwidths, the estimation results are indeed very similar.

6.2 Estimated Intra-Household Effects

Based on the estimate parameters $(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\gamma}})$, I compute the marginal intra-household effect for each individual according the formula (7). Table 6 lists the summary statistics for the distribution of the intra-household effects in the population for specifications (B), (C), and (D). By using the estimated coefficients under the preferred specification in Column (D), Figure 1 shows the estimated probability density of the intra-household effect. The estimated effects are positive for 99.49% of the individuals. On average, the effect increases subscription by 13.05 percentage points, with a standard deviation of 6.73 percentage points. This is a substantial effect when comparing with the average subscription rate 51.77%. When one household member chooses to subscribe, its average effect on the other member is equivalent to the effect caused by increasing the other member's own individual annual income by 0.484 million TWD (equal to

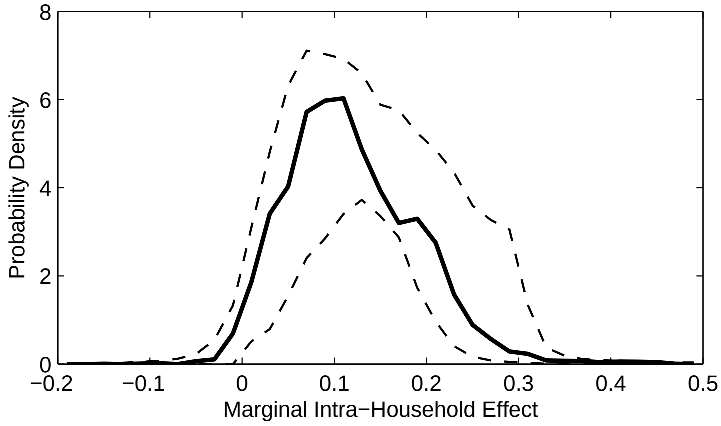

Figure 1: Probability density of the estimated marginal intra-household effects. Dashed lines represents 95% confidence intervals computed from 200 bootstrap draws.

14,059 USD) and holding other observed characteristics fixed. The existence of positive intra-household effects suggests the existence of network effects for cellular phone service within a household.

While there exists moderately large marginal intra-household effect for an individual, the probability of multiple Nash equilibria in a household is relatively small. The estimated parameters imply that the subscription rate would rise from 51.11% to 52.79% under full coordination among household members. On the other hand, if consumers always fail to coordinate, the penetration rate would drop from 51.77% to 51.11%. The difference of the subscription rate between perfect coordination and no coordination, which is also the probability of multiple Nash equilibria, is only 1.68% (= 52.79% − 51.11%).

Many previous researches on games with multiple equilibria impose an equilibrium selection rule by assuming that players always chooses an Pareto optimal equilibrium. However, my estimation indicates that the ratio of households which choose the Pareto optimal outcome when multiple Nash equilibria occur is only 39% (= (51.77% − 51.11%)/1.68%). In addition, the standard error for the estimated ratio is 12.22 percentage points. Consequently, this ratio is significantly different from one. Assuming Pareto optimality as an equilibrium selection rule is probably not innocuous when interaction between players is strong.

As Figure 1 illustrates, intra-household effects vary a lot across households. The estimated value of the vector-valued parameter $\boldsymbol{\gamma}$ explains the heterogeneity across households. The estimated signs are consistent with the intuition that intra-household effects are stronger when household members tend to spend less time together for family life. Specifically, the impact of household income on intra-household effects is both statistically and economically significant. Increasing household income by one standard deviation (602,761 TWD) raises the marginal intra-household effect by 2.9 percentage points. The marginal intra-household effect for those living in cities is about 6 percentage points higher than those living in towns and rural areas. This is probably because households with higher income and/or living in cities are more likely to spend more time on working and less time on family life. Unfortunately, I do not have data on working hours to verify this conjecture.

The number of children has a significantly negative effect, probably because families with more children tend to spend more time together to take care of children and hence reduce the need to talk on phones. Each additional child reduces the marginal intra-household effect by 3.5 percentage points. Besides, age difference reduces the intra-household effect. For instance, at the mean age difference (10.7 years), marginal intra-household effect is smaller than a household with identical-age members by 2.5 percentage points. Within-household network effect of cellular phone consumption decreases in the age difference, suggesting that individuals with similar age have stronger desire to talk to each other on cellular phones.

6.3 Estimated Direct Effects

I estimate the direct effect ($\boldsymbol{\beta}$) of both household-level and individual-level characteristics. Most household-level variables do not have significant impact on the subscription choice at the conventional significance level.

Individual income has a significantly positive effect on demand across specifications, but household income has a significant positive effect only in Column (A) and (B). Under the preferred specification (D), increasing individual income by one standard deviation (463,410 TWD) raises the subscription probability by 12.5 percentage points. This finding is in contrast with several previous studies on the demand for landline phone service. For example, Miravete (2002) finds household income has negative effects on landline phone service in two cities in Kentucky in 1986. Economides et al. (2008) also find a negative effect of income on the demand in New York State in the period 1999 – 2003.

As for the geographic variables, there is no significant difference in the direct effect across regions and across urbanization levels. Table 7 and Table 8 show the penetration rate of cellular service across regions and across urbanization levels. Although the penetration rates are higher in the North region and in cities, the demand for cellular phone service does not have a systematic relationship with the penetration rates. Consequently, there is no evidence showing the existence of network effects resulting

Table 7: Cellular Phone Ownership by Region

	North	Central	South
Cellular Phone per Household	2.0422	1.7941	1.6212
Cellular Phone per Person	0.5739	0.4892	0.4806

Table 8: Cellular Phone Ownership by Urbanization Level

	City	Town	Rural Area
Cellular Phone per Household	1.9522	1.5314	1.1450
Cellular Phone per Person	0.5557	0.4198	0.3489

from *geographic neighborhoods*. Furthermore, while there are four cellular phone carriers operating in the North region, there are five carriers operating in the Central and the South regions. More carriers in the Central and South regions provide more varieties to consumers. However, varieties of cellular phone service do not have significant effect on the demand.[16]

Lastly, the direct effects on demand resulting from individual characteristics are consistent with intuition. The demand is stronger for young, better-educated, and employed people. There is no significant gender difference. The estimation result is probably caused by the fact that young and better-educated people are more familiar with new technology so that they are more likely to adopt the new technology. Employed people usually spend more time away from home, so they are likely to have higher demand.

6.4 Implications for Targeted Marketing

The marginal intra-household effect is defined as the change in the subscription probability due to forcing the other household member from no subscription to subscription. In practice, firms cannot force consumers to change the subscription decision. Instead, firms can use targeted marketing to increase profits. To do so, they should charge a relatively lower price for consumers with lower demand. The estimated value of $\boldsymbol{\beta}$ indicates the direct effect of a consumer's own characteristics on his demand. Firms can conduct targeted marketing according to the estimated value. For network goods, a consumer's demand also depends on other household member's demand due to the intra-household effect. Therefore, other household member's characteristics would affect a consumer's demand through the interaction.

[16]It is possible that the effects caused by higher penetration rates and fewer varieties in the North region cancel out. Without more information, I cannot distinguish these two effects.

Consider an average household with two members Consumer A and Consumer B. The marginal intra-household effect for an average household is 13.05 percentage points. When a firm offers a special deal to Consumer A which increases his subscription probability by one percentage point, Consumer B's subscription probability would increase 0.13 percentage points through the intra-household effect. In other words, because of the intra-household effect, the impact of a targeted marketing strategy is magnified by 1.13. Now, consider a household with a stronger intra-household effect. Suppose its marginal intra-household effect is 26.51 percentage points, which is two standard deviations above the average. Then, when a special deal is offered to Consumer A, the impact of the targeted marketing strategy is magnified by 1.27. As pointed out in Subsection 6.2, intra-household effects are stronger for households living in a city and with higher income, fewer children, and less within-household age difference. Consequently, it is more important to account for intra-household interaction when using targeted marketing strategies to these households.

6.5 Estimated Results under Alternative Game Structures

The first column of Table 9 replicates Column (C) of Table 4, showing the estimation result under the assumption of a simultaneous-move non-cooperative game. The second column is the estimated coefficients under either a simultaneous-move cooperative game or a sequential-move game. The estimated coefficients are similar to those in the first column. Since the probability of multiple equilibria is less than 2% in a non-cooperative game, the equilibrium selection rule does not affect the estimation result very much in this market. Table 10 summarizes the estimated marginal intra-household effects, which are also similar under these different game structures.

7 Conclusion

This paper empirically analyzes heterogenous intra-household effects on the demand for cellular phone service under a game-theoretical framework to account for social networks and shows its implications for targeted marketing. Because of the interaction between household members, it is possible to have multiple Nash equilibria in a non-cooperative simultaneous-move game. Nonetheless, the model parameters are fully identified from the household survey data. I use a semiparametric maximum likelihood estimator to analyze the demand for cellular phone service in Taiwan. The intra-household effect of cellular phone service is positive on average, supporting the existence of network effect on cellular phone consumption

Table 9: Estimated Coefficients under Alternative Game Structures

	Non-Cooperative Game		Cooperative Game	
Characteristics	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ
constant	0.085	0.508*	0.170	0.458
	(0.211)	(0.299)	(0.219)	(0.298)
Household Income	0.118	0.092	0.067	0.145
	(0.170)	(0.132)	(0.195)	(0.141)
	[0.031]	[0.025]	[0.019]	[0.040]
Town	-0.036	-0.174*	-0.002	-0.204**
	(0.062)	(0.095)	(0.059)	(0.100)
	[-0.010]	[-0.047]	[-0.000]	[-0.056]
Rural	-0.041	-0.168	-0.027	-0.180
	(0.113)	(0.135)	(0.117)	(0.141)
	[-0.011]	[-0.045]	[-0.008]	[-0.050]
Central	0.030	-0.052	0.019	-0.041
	(0.056)	(0.073)	(0.064)	(0.077)
	[0.008]	[-0.014]	[0.005]	[-0.011]
South	-0.058	-0.009	-0.088	0.030
	(0.055)	(0.074)	(0.058)	(0.074)
	[-0.016]	[-0.002]	[-0.024]	[0.008]
Number of Children	0.041	-0.173***	0.046	-0.155***
	(0.055)	(0.053)	(0.067)	(0.063)
	[0.011]	[-0.047]	[0.013]	[-0.042]
Average Age		-0.046		-0.010
		(0.274)		(0.285)
		[-0.013]		[-0.003]
Average Education		0.092		0.055
		(0.112)		(0.125)
		[0.024]		[0.015]
Average Employment		0.002		0.085
		(0.093)		(0.096)
		[0.000]		[0.023]
Age Difference		-0.946***		-0.941***
		(0.253)		(0.220)
		[-0.255]		[-0.257]
Education Difference		0.047		0.036
		(0.061)		(0.055)
		[0.013]		[0.010]
Income Difference		-0.030		-0.048
		(0.164)		(0.136)
		[-0.008]		[-0.013]
Gender	-0.025		-0.051	
	(0.084)		(0.084)	
	[-0.007]		[-0.014]	
Age	-2.393***		-2.433***	
	(0.224)		(0.242)	
	[-0.646]		[-0.674]	
Education	0.570***		0.574***	
	(0.081)		(0.084)	
	[0.154]		[0.159]	
Employment	0.340***		0.267***	
	(0.074)		(0.075)	
	[0.098]		[0.078]	
Individual Income	0.862***		0.778***	
	(0.260)		(0.235)	
	[0.234]		[0.216]	
ρ	-0.477***		-0.462***	
	(0.087)		(0.093)	
Log-Likelihood	-2525.965		-2524.117	

Notes: Standard errors, computed from 50 bootstrap draws, are given in parentheses. Marginal effects, computed as average derivatives of the subscription probability except for for dummy variables whose effects are evaluated for a move from 0 to 1, are in square brackets. Superscripts ***, **, and *represent significance at 1%, 5%, and 10%, respectively. The sample size is 3,489 households.

Table 10: the Estimated Marginal Intra-Household Effects under Different Game Structures

	Non-Cooperative Game	Cooperative Game
Mean of Marginal Intra-Household Effect	11.72% (2.87%)	12.43% (3.60%)
Standard Deviation of Marginal Intra-Household Effect	6.27% (1.20%)	6.30% (1.39%)
Percentage of Positive Marginal Intra-Household Effect	99.05% (1.74%)	99.16% (3.12%)

Notes: Standard errors, computed from 50 bootstrap draws, are given in parentheses. There are two individuals in each of the 3,489 households.

within a household. This effect is heterogeneous across households. It increases in household income and is higher for households living in cities. But the effect decreases in the number of children and the age difference in a household, suggesting that the intra-household effect is stronger when household members are less likely to stay together for family life.

Positive consumption externality exists in many network goods. As a result, multiple Nash equilibria may occur in the consumption decision of these goods. Many previous empirical researches impose ad hoc equilibrium selection rules to overcome the multiplicity. The probability of multiple Nash equilibria is small in this cellular phone service market. The difference of the subscription rates between full coordination and no coordination is only 1.68%. Therefore, imposing assumptions on the equilibrium selection rule does not affect the estimation result very much. However, my estimation indicates that only 39% of households coordinate their subscription decisions to achieve their Pareto optimal outcome. Therefore, the equilibrium selection rule of achieving Pareto optimum imposed in many previous researches could potentially cause serious bias if the probability of multiple equilibria is large.

In the current research, I restrict my attention to households with only two members. An important extension is to include households with more than two individuals. Contrary to the two-member case, the parameters are only partially identified by inequality conditions. In addition, future extension can allow the intra-household effect to include unobserved factors and be heterogeneous across members within a household.

A Proof of Theorem 1

Proof. In equation (3), I have shown that the exact probabilities of $Y_i = 1$, which is denoted by $P_1(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$, can be obtained for any given observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$. Without loss of generality, assume $\beta_k > 0$. Let $(\widetilde{\boldsymbol{\beta}}, \widetilde{\boldsymbol{\gamma}}, \widetilde{\rho})$ be a vector different from $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$. The possible values of these two vectors can be divided into the following four possible cases.[17]

Case 1: $\widetilde{\boldsymbol{\beta}} \neq \boldsymbol{\beta}$ and $\widetilde{\beta}_k > 0$: As x_{i1k} goes to minus infinity for given x_{-i1k}, both $x_{i1k}\beta_k$ and $x_{i1k}\widetilde{\beta}_k$ go to minus infinity. Because X_2 has full rank, there exists $\mathbf{x}^*_{i2}$ such that $\mathbf{x}^{*\prime}_{i2}\boldsymbol{\beta} \neq \mathbf{x}^{*\prime}_{i2}\widetilde{\boldsymbol{\beta}}$. Consequently, as $x_{i1k} \to -\infty$,

$$\begin{aligned} P_1\left(\mathbf{x}_{i1}, \mathbf{x}^*_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho\right) &\simeq \Pr\left(\varepsilon_{i2} > -\mathbf{x}^{*\prime}_{i2}\boldsymbol{\beta}\right) \\ &\neq \Pr\left(\varepsilon_{i2} > -\mathbf{x}^{*\prime}_{i2}\widetilde{\boldsymbol{\beta}}\right) \simeq P_1\left(\mathbf{x}_{i1}, \mathbf{x}^*_{i2}, \mathbf{z}_i; \widetilde{\boldsymbol{\beta}}, \widetilde{\boldsymbol{\gamma}}, \widetilde{\rho}\right). \end{aligned}$$

This implies the parameters $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$ are identified when $\widetilde{\boldsymbol{\beta}} \neq \boldsymbol{\beta}$ and $\widetilde{\beta}_k > 0$.

Case 2: $\widetilde{\boldsymbol{\beta}} \neq \boldsymbol{\beta}$ and $\widetilde{\beta}_k < 0$: Since Z has full rank, there exists $\mathbf{z}^*_i$ such that $\mathbf{z}^{*\prime}_i\boldsymbol{\gamma} \neq \mathbf{z}^{*\prime}_i\widetilde{\boldsymbol{\gamma}}$ when $\widetilde{\boldsymbol{\gamma}} \neq \boldsymbol{\gamma}$. If the parameters are not identified, then

$$\begin{aligned} P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}^*_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho\right) &\simeq \Pr(\varepsilon_{i2} > -\mathbf{x}'_{i2}\boldsymbol{\beta}) \\ &= \Pr\left(\varepsilon_{i2} < -\mathbf{x}'_{i2}\widetilde{\boldsymbol{\beta}} - \mathbf{z}^{*\prime}_i\widetilde{\boldsymbol{\gamma}}\right) \simeq P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}^*_i; \widetilde{\boldsymbol{\beta}}, \widetilde{\boldsymbol{\gamma}}, \widetilde{\rho}\right). \end{aligned} \tag{11}$$

for any $\mathbf{x}_{i2}$ as $x_{i1k} \to -\infty$ for given x_{-i1k}, and

$$\begin{aligned} P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}^*_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho\right) &\simeq \Pr\left(\varepsilon_{i2} < -\mathbf{x}'_{i2}\boldsymbol{\beta} - \mathbf{z}^{*\prime}_i\boldsymbol{\gamma}\right) \\ &= \Pr\left(\varepsilon_{i2} > -\mathbf{x}'_{i2}\widetilde{\boldsymbol{\beta}}\right) \simeq P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}^*_i; \widetilde{\boldsymbol{\beta}}, \widetilde{\boldsymbol{\gamma}}, \widetilde{\rho}\right). \end{aligned} \tag{12}$$

for any $\mathbf{x}_{i2}$ as $x_{i1k} \to +\infty$ for given x_{-i1k}. Since ε_{i2} is a symmetric distribution with zero mean, Equations (11) and (12) together imply

$$\mathbf{x}'_{i2}\boldsymbol{\beta} = -\mathbf{x}'_{i2}\widetilde{\boldsymbol{\beta}} - \mathbf{z}^{*\prime}_i\widetilde{\boldsymbol{\gamma}} = \mathbf{x}'_{i2}\boldsymbol{\beta} + \mathbf{z}^{*\prime}_i\boldsymbol{\gamma} - \mathbf{z}^{*\prime}_i\widetilde{\boldsymbol{\gamma}} \neq \mathbf{x}'_{i2}\boldsymbol{\beta}.$$

[17] Case 1 and Case 2 consider any parameter values such that $\widetilde{\boldsymbol{\beta}} \neq \boldsymbol{\beta}$, regardless the values of $\boldsymbol{\gamma}$, ρ, $\widetilde{\boldsymbol{\gamma}}$, and $\widetilde{\rho}$. Case 3 considers any parameter values such that $\widetilde{\boldsymbol{\beta}} = \boldsymbol{\beta}$ but $\widetilde{\boldsymbol{\gamma}} \neq \boldsymbol{\gamma}$, regardless the values of rho and $\tilde{\rho}$. Hence, these four cases exhaust all possible values of these two vectors.

This is a contradiction. Therefore, equations (11) and (12) cannot hold together, implying the parameters $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$ are identified when $\widetilde{\boldsymbol{\beta}} \neq \boldsymbol{\beta}$, $\widetilde{\beta}_k < 0$, and $\widetilde{\boldsymbol{\gamma}} \neq \boldsymbol{\gamma}$.

If $\widetilde{\boldsymbol{\gamma}} = \boldsymbol{\gamma}$, either equation (11) or (12) implies that $\mathbf{x}_{i2}'(\boldsymbol{\beta} + \widetilde{\boldsymbol{\beta}}) + \mathbf{z}_i^{*\prime}\boldsymbol{\gamma} = 0$ holds for any $(\mathbf{x}_{i2}, \mathbf{z}_i)$. This contradicts with the fact that X_2 and Z both have full rank. Hence, $(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$ are also identified when $\widetilde{\boldsymbol{\beta}} \neq \boldsymbol{\beta}$, $\widetilde{\beta}_k < 0$, and $\widetilde{\boldsymbol{\gamma}} = \boldsymbol{\gamma}$.

Case 3: $\widetilde{\boldsymbol{\beta}} = \boldsymbol{\beta}$ but $\widetilde{\boldsymbol{\gamma}} \neq \boldsymbol{\gamma}$: Because $\beta_k > 0$, I know $\widetilde{\beta}_k > 0$. Let x_{i1k} go to positive infinity. Both $x_{i1k}\beta_k$ and $x_{i1k}\widetilde{\beta}_k$ go to positive infinity. Because Z has full rank, there exists $\mathbf{z}_i^{**}$ such that $\mathbf{z}_i^{**\prime}\boldsymbol{\gamma} \neq \mathbf{z}_i^{**\prime}\widetilde{\boldsymbol{\gamma}}$. As $x_{i1k} \to +\infty$, for any $\mathbf{x}_{i2}$, I have $\mathbf{x}_{i2}'\boldsymbol{\beta} = \mathbf{x}_{i2}'\widetilde{\boldsymbol{\beta}}$ and

$$\begin{aligned} P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i^{**}; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho\right) &\simeq \Pr\left(\varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i^{**\prime}\boldsymbol{\gamma}\right) \\ &\neq \Pr\left(\varepsilon_{i2} < -\mathbf{x}_{i2}'\widetilde{\boldsymbol{\beta}} - \mathbf{z}_i^{**\prime}\widetilde{\boldsymbol{\gamma}}\right) \simeq P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i^{**}; \widetilde{\boldsymbol{\beta}}, \widetilde{\boldsymbol{\gamma}}, \widetilde{\rho}\right). \end{aligned}$$

Therefore, I can identify the parameters when $\widetilde{\boldsymbol{\beta}} = \boldsymbol{\beta}$ but $\widetilde{\boldsymbol{\gamma}} \neq \boldsymbol{\gamma}$.

Case 4: $(\widetilde{\boldsymbol{\beta}}, \widetilde{\boldsymbol{\gamma}}) = (\boldsymbol{\beta}, \boldsymbol{\gamma})$ but $\widetilde{\rho} \neq \rho$: For $\mathbf{z}_i'\boldsymbol{\gamma} > 0$, I have

$$\frac{\partial P_1(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)}{\partial \rho} = -\frac{e^{-\frac{(\mathbf{x}_{i1}'\boldsymbol{\beta} + \mathbf{z}_i'\boldsymbol{\gamma})^2 + (\mathbf{x}_{i2}'\boldsymbol{\beta})^2 - 2\rho(\mathbf{x}_{i1}'\boldsymbol{\beta} + \mathbf{z}_i'\boldsymbol{\gamma})(\mathbf{x}_{i2}'\boldsymbol{\beta})}{2(1-\rho^2)}}}{\pi\sqrt{1-\rho^2}} < 0.$$

Similarly, for $\mathbf{z}_i'\boldsymbol{\gamma} < 0$, I can obtain

$$\begin{aligned} &\frac{\partial P_1(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)}{\partial \rho} = \\ &\quad -\frac{e^{-\frac{(\mathbf{x}_{i1}'\boldsymbol{\beta})^2 + (\mathbf{x}_{i2}'\boldsymbol{\beta})^2 - 2\rho(\mathbf{x}_{i1}'\boldsymbol{\beta})(\mathbf{x}_{i2}'\boldsymbol{\beta})}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}} - \frac{e^{-\frac{(\mathbf{x}_{i1}'\boldsymbol{\beta} + \mathbf{z}_i'\boldsymbol{\gamma})^2 + (\mathbf{x}_{i2}'\boldsymbol{\beta} + \mathbf{z}_i'\boldsymbol{\gamma})^2 - 2\rho(\mathbf{x}_{i1}'\boldsymbol{\beta} + \mathbf{z}_i'\boldsymbol{\gamma})(\mathbf{x}_{i2}'\boldsymbol{\beta} + \mathbf{z}_i'\boldsymbol{\gamma})}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}} < 0. \end{aligned}$$

Therefore, ρ can be identified from the data when $(\widetilde{\boldsymbol{\beta}}, \widetilde{\boldsymbol{\gamma}}) = (\boldsymbol{\beta}, \boldsymbol{\gamma})$. □

B Robustness Checks

In this appendix, I consider alternative choices on the bandwidth used in the kernel regression. The estimation results presented in the main text are based on the Scott's rule, which suggests the bandwidth 0.682. To check the robustness of the results, I consider several alternative bandwidths, including 0.5, 1, and 2. The estimated coefficients under alternative bandwidths are shown in Table 11. Most estimated

Table 11: Robustness Checking with Alternative Bandwidths in Kernel Regression

	bandwidth=0.5		bandwidth=0.682		bandwidth=1		bandwidth=2	
Characteristics	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ
constant	-0.085	0.692**	0.085	0.508*	0.065	0.580*	0.087	0.534
	(0.222)	(0.291)	(0.211)	(0.299)	(0.205)	(0.327)	(0.213)	(0.328)
Household Income	0.036	0.177	0.118	0.092	0.056	0.151	0.068	0.155
	(0.155)	(0.128)	(0.170)	(0.132)	(0.170)	(0.132)	(0.166)	(0.135)
	[0.010]	[0.048]	[0.031]	[0.025]	[0.015]	[0.041]	[0.018]	[0.042]
Town	-0.059	-0.154	-0.036	-0.174*	-0.075	-0.133	-0.060	-0.142
	(0.061)	(0.090)	(0.062)	(0.095)	(0.060)	(0.095)	(0.060)	(0.096)
	[-0.016]	[-0.042]	[-0.010]	[-0.047]	[-0.020]	[-0.036]	[-0.016]	[-0.039]
Rural	-0.075	-0.125	-0.041	-0.168	-0.134	-0.093	-0.107	-0.096
	(0.111)	(0.136)	(0.113)	(0.135)	(0.118)	(0.137)	(0.119)	(0.139)
	[-0.020]	[-0.034]	[-0.011]	[-0.045]	[-0.036]	[-0.025]	[-0.029]	[-0.026]
Central	0.019	-0.048	0.030	-0.052	0.029	-0.060	0.036	-0.062
	(0.054)	(0.077)	(0.056)	(0.073)	(0.066)	(0.081)	(0.068)	(0.080)
	[0.005]	[-0.013]	[0.008]	[-0.014]	[0.008]	[-0.016]	[0.010]	[-0.017]
South	-0.078	0.001	-0.058	-0.009	-0.047	-0.022	-0.051	-0.018
	(0.050)	(0.068)	(0.055)	(0.074)	(0.059)	(0.075)	(0.061)	(0.076)
	[-0.021]	[0.000]	[-0.016]	[-0.002]	[-0.013]	[-0.006]	[-0.014]	[-0.005]
Number of Children	0.060	-0.199***	0.041	-0.173***	0.047	-0.183***	0.046	-0.180***
	(0.058)	(0.056)	(0.055)	(0.053)	(0.056)	(0.052)	(0.056)	(0.054)
	[0.016]	[-0.054]	[0.011]	[-0.047]	[0.013]	[-0.050]	[0.013]	[-0.049]
Average Age		-0.228		-0.046		-0.104		-0.102
		(0.259)		(0.274)		(0.285)		(0.261)
		[-0.062]		[-0.013]		[-0.028]		[-0.027]
Average Education		0.016		0.092		0.063		0.058
		(0.109)		(0.112)		(0.114)		(0.113)
		[0.004]		[0.024]		[0.017]		[0.016]
Average Employment		-0.071		0.002		-0.019		-0.016
		(0.091)		(0.093)		(0.097)		(0.095)
		[-0.019]		[0.000]		[-0.005]		[-0.004]
Age Difference		-1.001***		-0.946***		-0.961***		-0.950***
		(0.252)		(0.253)		(0.261)		(0.262)
		[-0.270]		[-0.255]		[-0.260]		[-0.256]
Education Difference		0.064		0.047		0.046		0.062
		(0.061)		(0.061)		(0.063)		(0.063)
		[0.017]		[0.013]		[0.013]		[0.017]
Income Difference		-0.037		-0.030		-0.039		-0.047
		(0.152)		(0.164)		(0.166)		(0.159)
		[-0.010]		[-0.008]		[-0.011]		[-0.013]
Gender	0.006		-0.025		-0.022		-0.027	
	(0.081)		(0.084)		(0.083)		(0.085)	
	[0.002]		[-0.007]		[-0.006]		[-0.007]	
Age	-2.181***		-2.393***		-2.332***		-2.385***	
	(0.253)		(0.224)		(0.228)		(0.226)	
	[-0.591]		[-0.646]		[-0.635]		[-0.646]	
Education	0.651***		0.570***		0.589***		0.616***	
	(0.074)		(0.081)		(0.079)		(0.079)	
	[0.177]		[0.154]		[0.161]		[0.167]	
Employment	0.411***		0.340***		0.350***		0.343***	
	(0.064)		(0.074)		(0.076)		(0.077)	
	[0.120]		[0.098]		[0.102]		[0.099]	
Individual Income	0.808***		0.862***		0.831***		0.816***	
	(0.225)		(0.260)		(0.273)		(0.266)	
	[0.219]		[0.234]		[0.226]		[0.221]	
ρ	-0.513***		-0.477***		-0.521***		-0.480***	
	(0.088)		(0.087)		(0.112)		(0.106)	
Log-Likelihood	-2525.947		-2525.965		-2526.126		-2525.977	

Notes: Standard errors, computed from 50 bootstrap draws, are given in parentheses. Marginal effects, computed as average derivatives of the subscription probability except for for dummy variables whose effects are evaluated for a move from 0 to 1, are in square brackets. Superscripts ***, **, and *represent significance at 1%, 5%, and 10%, respectively. The sample size is 3489 households.

Table 12: the Estimated Marginal Intra-Household Effects under Alternative Bandwidths

	bandwidth=0.5	bandwidth=0.682	bandwidth=1	bandwidth=2
Mean of Marginal Intra-Household Effect	13.10% (3.02%)	11.72% (2.87%)	13.01% (3.43%)	11.76% (3.23%)
Standard Deviation of Marginal Intra-Household Effect	6.66% (1.10%)	6.27% (1.20%)	6.47% (1.32%)	6.17% (1.28%)
Percentage of Positive Marginal Intra-Household Effect	99.45% (2.80%)	99.05% (1.74%)	99.56% (2.20%)	99.14% (0.87%)

Notes: Standard errors, computed from 50 bootstrap draws, are given in parentheses. There are two individuals in each of the 3489 households.

coefficients are not sensitive to the choice of the bandwidth. In addition, Table 12 shows that the distribution of the estimated marginal intra-household effects is also robust to alternative choices of the bandwidths.

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References

Bajari, P., Fox, J. T., & Ryan, S. (2008). Evaluating wireless carrier consolidation using semiparametric demand estimation. *Quantitative Marketing and Economics 6*, 299–338.

Bajari, P., Hong, H., & Ryan, S. (2010). Identification and estimation of a discrete game of complete information. *Econometrica 78*, 1529–1568.

Berry, S. & Reiss, P. (2007). Empirical models of entry and market structure. In M. Armstrong and R. H. Porter (Eds.), *Handbook of Industrial Organization*, Volume 3, Chapter 29. North-Holland.

Birke, D. & Swann, G. M. P. (2006). Network effects and the choice of mobile phone operator. *Journal of Evolutionary Economics 16*, 65–84.

Bresnahan, T. F. & Reiss, P. C. (1990). Entry in monopoly markets. *Review of Economic Studies 57*, 531–553.

Bresnahan, T. F. & Reiss, P. C. (1991). Empirical models of discrete games. *Journal of Econometrics 48*, 57–81.

Browning, M., Bourguignon, F., Chaippori, P.-A., & Lechene, V. (1994). Income and outcomes: A structural model of intrahousehold allocation. *Journal of Political Economics 102*, 1067–1096.

Chernozhukov, V., Hong, H., & Tamer, E. (2007). Estimation and confidence regions for parameter sets in econometric models. *Econometrica 75*, 1243–1284.

Ciliberto, F. & Tamer, E. T. (2009). Market structure and multiple equilibria in the airline industry. *Econometrica 77*, 1791–1828.

Doganoglu, T. & Grzybowski, L. (2007). Estimating network effects in mobile telephony in germany. *Information Economics and Policy 19*, 65–79.

Duffy-Deno, K. T. (2001). Demand for additional telephone lines: An empirical note. *Information Economics and Policy 13*, 283–299.

Economides, N., Seim, K., & Viard, B. V. (2008). Quantifying the benefits of entry into local phone service. *RAND Journal of Economics 39*, 699–730.

Farrell, J. & Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. In M. Armstrong and R. Porter (Eds.), *Handbook of Industrial Organization*, Volume 3. North-Holland/Elsevier.

Grzybowski, L. (2008). Estimating switching costs in mobile telephony in the UK. *Journal of Industry, Competition and Trade 8*, 113–132.

Grzybowski, L. & Pereira, P. (2011). Subscription choices and switching costs in mobile telephony. *Review of Industrial Organization 38*, 23–42.

Hartmann, W. R. (2010). Demand estimation with social interactions and the implications for targeted marketing. *Marketing Science 29*, 585–601.

Huang, C.-I. (2008). Estimating demand for cellular phone service under nonlinear pricing. *Quantitative Marketing and Economics 6*, 371–413.

Iyengar, R. (2004). A structural demand analysis for wireless services under nonlinear pricing schemes. Mimeo. University of Pennsylvania.

Jia, P. (2008). What happens when Wal-Mart comes to town: An empirical analysis of the discount retailing industry. *Econometrica 76*, 1263–1316.

Madden, G. & Simpson, M. (1997). Residential broadband subscription demand: an econometric analysis of australian choice experiment. *Applied Economics 29*, 1073–1078.

Miravete, E. J. (2002). Estimating demand for local telephone service with asymmetric information and optional calling plans. *Review of Economic Studies 69*, 943–971.

Pakes, A., Porter, J., Ho, K., & Ishii, J. (2006). Moment inequalities and their application. Mimeo. Harvard University.

Rappoport, P. N. & Taylor, L. D. (1997). Toll price elasticities estimated from a sample of U.S. residential telephone bills. *Information Economics and Policy 9*, 51–70.

Rodini, M., Ward, M. R., & Woroch, G. A. (2003). Going mobile: Substitutability between fixed and mobile access. *Bell Journal of Economics and Management Science 27*, 457–476.

Rohlfs, J. (1974). A theory of independent demand for a communications service. *Bell Journal of Economics and Management Science 5*, 16–37.

Scott, D. W. (1992). *Multivariate Density Estimation: Theory, Practice, and Visualization.* New York: John Wiley & Sons, Inc.

Solvason, D. L. (1997). Cross-sectional analysis of residential telephone subscription in canada using 1994 data. *Information Economics and Policy 99*, 30–53.

Tamer, E. (2003). Incomplete simultaneous discrete response model with multiple equilibria. *Review of Economic Studies 70*, 147–165.

Train, K. E., Ben-Akiva, M., & Atherton, T. (1989). Consumption patterns and self-selecting tariffs. *Review of Economics and Statistics 71*, 62–73.

Train, K. E., McFadden, D. L., & Ben-Akiva, M. (1987). The demand for local telephone service: A fully discrete model of residential calling patterns and service choices. *RAND Journal of Economics 18*, 109–123.

Vermeulen, F. (2002). Collective household models: Principles and main results. *Journal of Economic Surveys 16*, 533–564.

Vitorino, M. A. (2011). Empirical entry games with complementarities: An application to the shopping center industry. Mimeo. University of Pennsylvania.