行政院國家科學委員會專題研究計畫 成果報告

家戶內對於電信服務之消費外部性
研究成果報告(精簡版)

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計畫主持人：黃景沂

計畫參與人員：碩士級-專任助理：石雅茹

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行政院國家科學委員會補助專題研究計畫成果報告

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執行單位: 國立台灣大學經濟學系暨研究所

中華民國96年10月24日

Abstract

I propose a game-theoretical model to estimate demand for telephone service, accounting for intra-household interaction among household members. Although multiple Nash equilibria of subscription decisions may exist in a household, the model parameters are identified from the household-level data for any given correlation coefficient of unobserved characteristics. Because the correlation of unobserved characteristics is identified only through functional form assumption, I use the correlation of observed ones to determine its magnitude. I analyze the demand in Taiwan by a semiparametric maximum likelihood estimation. The distribution of the estimated intra-household effects of cellular phone service stochastically dominates that of landline phone service. The estimated effects of landline phone service are negative for all households. However, my estimation is inconclusive about the sign of effects of cellular phone consumption for most households.

我提出了一個賽局模型來估計電信需求, 在此模型當中, 我考慮了家户成員之間相互的影響。儘管在此模型之下, 使用電信服務的決定可能有多重均衡存在, 不過只要給定了對於未觀察到個人特徵的相關係數, 此模型的參數即可 identified。然而, 此一相關係數卻無法直接透過資料來 idenfity, 所以我提出的估計方法, 利用可觀察到個人特徵的相關係數來決定其大小。我利用本研究提出的估計方法來研究台灣的電信需求, 發現行動電話服務的家户內之效果, 要高於市內電話的家户內效果。市內電話的家户內效果對於每個人都是負值。相反的, 行動電話服務的家户內之效果是正值或者是負值, 並無法從資料中得到結論。

Keywords: telephone demand, semiparametric estimation, multiple Nash equilibria, consumption externality

報告内容

1 Introduction

Standard microeconomic theory analyzes consumer behavior based on individual preferences. When more than one person lives in a household, we need to take into account the intra-household allocation of resources and consumption externalities among household members. In this study, I use a game-theoretical framework to estimate demand for telephone service and analyze intra-household effect of the subscription decision. There is a rich literature on estimating household demand for telecommunication service. Generally, these studies use household-level survey data. Nonetheless, each household is treated as a single decision-maker in the estimation. Only household heads' individual characteristics are included in the demand estimation. 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.[1] This assumption is unlikely to be true in most households.

As Browning, Bourguignon, Chaippori, and Lechene (1994) point out, household behavior depends on intra-household interactions unless we impose some restrictive hypotheses such as transferable utilities. They propose 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 efficient in the bargaining process. Using data on couples with no kids, they find that the allocation of expenditure depends on the relative incomes and 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.

I consider a model of binary subscription choice. When there is only a single person in a household, this model reduces to a standard discrete choice model. When more than one person lives in a household, the decision would in general depend on the choices of other members. For example, if the husband has a cellular phone, the wife may have a stronger desire to own a cellular phone as well. There are several potential positive spillover effect. First, the husband can be contacted by phone even when he is away from a landline phone. This increases the wife's demand for phone service (the direct network effect). Second, the husband's knowledge of cellular service reduces the wife's information cost of subscription decision (the indirect network effect). Third, when the price of a cellular-to-cellular phone call is lower than a landline-to-cellular phone call[2], the wife pays less for a call from a cellular phone than from a landline phone. Besides, carriers often offer family plans which lowers the subscription fee for a second cellular phone (the price effect) On the other hand, the spillover 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 other person's cellular phone. Whether the net effect is positive or negative is an empirical issue. However, because it is more difficult to share the usage of a cellular phone, positive effects are more likely to dominate for cellular phone service than for landline service. My empirical findings confirms this conjecture.

In the current study, I restrict my attention to households with two members. Each of the two members makes a binary choice on the subscription of telephone service. My model is similar to entry models in the industrial organization literature, such as Bresnahan and Reiss (1990). However, the effects between two firms in an entry model are always negative. The entrance of one firm reduces the profit of the other firm. Their entry decisions must be strategic substitutes. For household consumption behavior, effects may be either positive or negative. When they are positive, the decisions are strategic complements. I do not restrict the sign of intra-household effects in estimation. The sign can vary across households. I will investigate how the effects affected by household characteristics.

There are two primary difficulties in the estimation. The first issue is about multiple Nash equilibria, and the second one is to identify the correlation of unobserved individual characteristics. When intra-household effect is negative, the equilibrium number of subscribers in a household is unique as in Bresnahan and Reiss (1990)'s entry model. On the contrary, multiple Nash equilibria are possible when intra-household effect is positive. To deal with multiple Nash equilibria, we can impose rules to select among these equilibria. For example, in a recent paper, Bajari, Hong, and Ryan (2007) suggest a simulation-based method to estimate the selection rule. The econometric model in this study is an extension of Tamer (2003). His approach uses a semiparametric

[1] Train, McFadden, and Ben-Akiva (1987) and Train, Ben-Akiva, and Atherton (1989) only consider aggregate household income. In the estimation of demand for local telephone service under optional rate plans, Miravete (2002) includes several household-level characteristics. However, his empirical analysis only accounts for household head's individual characteristics, but not other members' characteristics. Many previous researches (Rappoport and Taylor, 1997; Solvason, 1997; Madden and Simpson, 1997; Duffy-Deno, 2001; Rodini, Ward, and Woroch, 2003; Economides, Seim, and Viard, 2006) use similar approach in estimating telephone demand.

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

estimation of the data to determine the selection among multiple equilibria. I show that the parameters in the demand model can be pointwise identified for any given correlation of unobserved individual characteristics.

The unobserved characteristics of individuals within a household are unlikely to be independent. Although the correlation can be formally identified without an instrumental variable, the identification is only based on the functional form specification, not from the data. I impose the idea developed in Altonji, Elder, and Taber (2005) to gauge the within-household correlation of unobserved characteristics from the correlation of observed ones. The true value of the correlation depends on the data structure. On the one extreme, if the set of observed characteristics includes all relevant ones, the within-household correlation of unobserved characteristics is zero. On the other extreme, if observed characteristics are randomly chosen from all possible factors, the correlation of these characteristics is identical to the correlation of the unobserved ones. In general, the selection of observable characteristics is between these two extreme cases. Consequently, I require the correlation of unobserved characteristics to be bounded by the correlation of observed characteristics and zero. This requirement allows me to estimate the upper and lower bounds of intra-household effects for each household.

In the next section, I introduce the econometric model and discuss the difficulties regrading demand estimation. In Section 3, I present my empirical results on the consumption of telephone service in Taiwan. Concludes are in the final section.

2 Econometric Model

The presence of intra-household effect implies that consumption depends on the decision of other household members. In this section, I present a static discrete response model which is an extension of the probit model. I restrict my attention to households with two members and show that, conditional on a given correlation coefficient of unobserved characteristics, the model parameters are fully identified despite the existence of multiple Nash equilibria in a noncooperative game between two household members. However, the correlation of unobserved characteristics can only be identified from functional form specification, I discuss my approach to deal with this problem in the final part of this section.

2.1 Discrete Response Model

For household i, there are two individual members $j \in \{1, 2\}$. All characteristics of each member are observed by both members. However, only some of the characteristics are observed by the econometrician. Denote the *observed characteristics* of member j by a vector $\mathbf{x}_{ij}$ and the *unobserved characteristics* by a scalar ε_{ij}. Let $\mathbf{z}_i$ denote the vector of *household-level characteristics*. Since some of the individual-level characteristics are common to both members(such as household income, residence location) the vector of individual-level characteristics $\mathbf{x}_{ij}$ may have overlapping elements with the vector of household-level characteristics $\mathbf{z}_i$. To identify the model parameters, however, at least one of the elements in the vector $\mathbf{x}_{ij}$ (such as member i's age) is not a household-level characteristic. Furthermore, both $\mathbf{x}_{ij}$ and $\mathbf{z}_i$ may contain a constant term.

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 a telephone service I will estimate the demand for cellular phone service and for landline phone service separately. The demand is characterized by

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

where $(3 - j)$ is the index for the other member in the household. Let $Y_i = y_{i1} + y_{i2}$ be the total number of subscribers in the household.

The terms in the first bracket of equation (1) represents the *direct effect of consumption choice*. The term in the second bracket, $\mathbf{z}'_i\boldsymbol{\gamma}$, is the *intra-household effect*. It is reciprocal between these two members. I normalize the effect to be zero if the other member do not subscribe. The intra-household effect is assumed to be completely captured by observed characteristics $\mathbf{z}_i$.[3] My model reduces to the standard probit model if the intra-household effect vanishes ($\boldsymbol{\gamma} = 0$).

The unobserved characteristics $(\varepsilon_{i1}, \varepsilon_{i2})$ are assumed to be jointly normally distributed, independently across households.

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

[3] In theory, I can extend the model to add an unobserved part on the intra-household effect so that it is expressed as $x'_i\boldsymbol{\gamma} + \eta_i$. Nonetheless, the extended model is computationally intensive. Moreover, when I estimate the model under no unobserved characteristics, the variance of the intra-household effects on consumption of cellular phone service is only 0.019 of the variable of the own effects. This suggests the magnitude of the intra-household effects is much smaller than that of the own effects. Therefore, I decide to ignore the unobserved intra-household effects for the rest of the report.

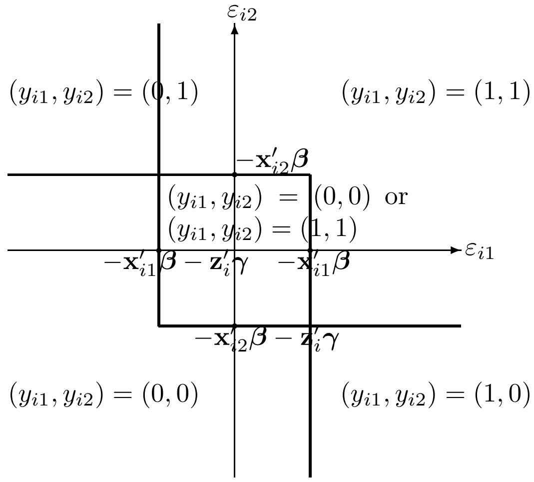

Figure 1: Simultaneous-move non-cooperative game for positive externality

The variance of ε_{ij} is normalized to one. The correlation coefficient ρ in (2) is identified only through functional form specification, not from observed data. It cannot be accurately estimated. As a result, I apply the idea developed in Altonji et al. (2005) and use the correlation of observed characteristics to provide information about the correlation of unobserved ones. See Section 2.4 below for more details about assumptions on the unobserved factors.

2.2 Nash Equilibria

Consider a simultaneous-move non-cooperative game.[4] This is similar to the incomplete model discussed in Tamer (2003). Figure 1 shows the set of equilibria for positive intra-household effect ($\mathbf{z}_i'\boldsymbol{\gamma} > 0$) conditional on observed characteristics $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ and unobserved characteristics $(\varepsilon_{i1}, \varepsilon_{i2})$. There are multiple Nash equilibria when $(\varepsilon_{i1}, \varepsilon_{i2}) \in (-\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_{i1}'\boldsymbol{\beta}) \times (-\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}, -\mathbf{x}_{i2}'\boldsymbol{\beta})$. Both $(y_{i1}, y_{i2}) = (0, 0)$ and $(y_{i1}, y_{i2}) = (1, 1)$ are equilibria in this region. Nonetheless, the model predicts the exact probability for $(y_{i1}, y_{i2}) = (0, 1)$ and $(y_{i1}, y_{i2}) = (1, 0)$. The probability of the event $(0, 0)$ is bounded by

$$\Pr\left(\{\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta}\} \cup \{\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}\} | \mathbf{z}_i'\boldsymbol{\gamma} > 0\right)$$

and

$$\Pr(\varepsilon_{i1} < -\mathbf{x}_{i1}'\boldsymbol{\beta},\ \varepsilon_{i2} < -\mathbf{x}_{i2}'\boldsymbol{\beta} | \mathbf{z}_i'\boldsymbol{\gamma} > 0).$$

On the other hand, when the effect is negative ($\mathbf{z}_i'\boldsymbol{\gamma} < 0$), there are multiple equilibria of $(0, 1)$ and $(1, 0)$ if $(\varepsilon_{i1}, \varepsilon_{i2}) \in (-\mathbf{x}_{i1}'\boldsymbol{\beta}, -\mathbf{x}_{i1}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma}) \times (-\mathbf{x}_{i2}'\boldsymbol{\beta}, -\mathbf{x}_{i2}'\boldsymbol{\beta} - \mathbf{z}_i'\boldsymbol{\gamma})$. (See Figure 2.) The model gives the exact probabilities of $(y_{i1}, y_{i2}) = (0, 0)$ and $(y_{i1}, y_{i2}) = (1, 1)$.

Regardless the sign of intra-household effect, the exact probability of observing 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 obtain from the model.

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

where $\mathbf{1}\{\cdot\}$ denotes an 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.[5] 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 $1 - \Pr(Y_i = 0 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i) - \Pr(Y_i = 1 | \mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$. The probability of no subscriber in a household is bounded in an interval. The upper bound occurs when individuals

[4] The set of Nash equilibria under a cooperative game is included in the set of Nash equilibria under a non-cooperative game. Consequently, the results under a cooperative game can be viewed as imposing an equilibrium selection rule on the results under a non-cooperative game.

[5] 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 in equilibrium.

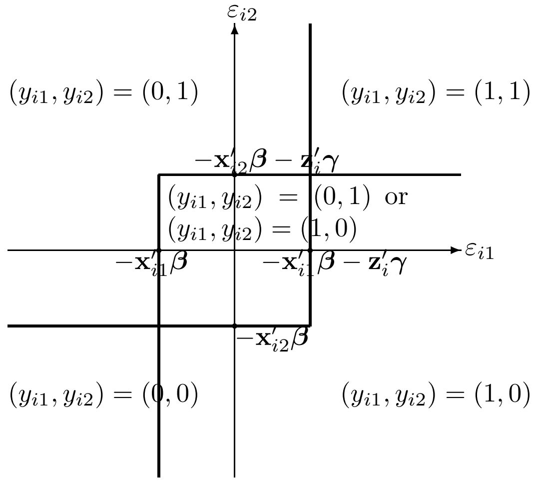

Figure 2: Simultaneous-move noncooperative game for negative externality

always fail to coordinate their decisions in the event of multiple Nash equilibria.

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

The lower bound is achieved when individuals can perfectly coordinate.

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

2.3 Identification

Although there are multiple Nash equilibrium in my econometric model, the parameters can be pointwise identified as long as the correlation coefficient of the unobserved characteristics ρ in (2) is known. My model is similar to Tamer (2003), which 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. The following theorem is an extension of Theorem 1 in Tamer (2003).

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 $\mathbf{x}_{-i1k} = (x_{i11}, \ldots, x_{i1,k-1}, x_{i1,k+1}, \ldots, x_{i1K})$. Then the parameter vectors, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, are identified for any given covariance matrix of unobserved characteristics if the matrices $\{\mathbf{x}_{i1} : i = 1\ldots, N\}$, $\{\mathbf{x}_{i2} : i = 1, \ldots, N\}$, and $\{\mathbf{z}_i : i = 1, \ldots, N\}$ have full rank.*

2.4 Unobserved Characteristics

As I mentioned at the beginning of this section, the observed data cannot truly identify the covariance matrix of the unobserved characteristics (2). In fact, the correlation coefficient ρ can not be separately identified from the mean of consumption externality. To demonstrate this, consider the case $\mathbf{z}_i'\boldsymbol{\gamma} = \gamma_0$ is a constant for all household.

For positive externality $\gamma_0 > 0$,

$$\begin{aligned} & P_1(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \gamma_0, \rho) \\ ={}& \Pr(\mathbf{x}_{i1}'\boldsymbol{\beta} + \gamma_0 + \varepsilon_{i1} < 0, \mathbf{x}_{i2}'\boldsymbol{\beta} + \varepsilon_{i2} > 0) + \Pr(\mathbf{x}_{i1}'\boldsymbol{\beta} + \varepsilon_{i1} > 0, \mathbf{x}_{i2}'\boldsymbol{\beta} + \gamma_0 + \varepsilon_{i2} < 0) \\ ={}& \int_{-\infty}^{-\mathbf{x}_{i1}'\boldsymbol{\beta} - \gamma_0} \int_{-\infty}^{\mathbf{x}_{i2}'\boldsymbol{\beta}} \frac{e^{-\frac{\varepsilon_{i1}^2 + \varepsilon_{i2}^2 + 2\rho\varepsilon_{i1}\varepsilon_{i2}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}} \, d\varepsilon_{i2}\, d\varepsilon_{i1} + \int_{-\infty}^{\mathbf{x}_{i1}'\boldsymbol{\beta}} \int_{-\infty}^{-\mathbf{x}_{i2}'\boldsymbol{\beta} - \gamma_0} \frac{e^{-\frac{\varepsilon_{i1}^2 + \varepsilon_{i2}^2 + 2\rho\varepsilon_{i1}\varepsilon_{i2}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}} \, d\varepsilon_{i2}\, d\varepsilon_{i1}. \end{aligned}$$

Compute the partial derivatives with respect to ρ and γ_0, respectively.[6]

$$\frac{\partial P_1(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\gamma_0,\rho)}{\partial\rho} = -\frac{e^{-\frac{(\mathbf{x}'_{i1}\boldsymbol{\beta}+\gamma_0)^2+(\mathbf{x}'_{i2}\boldsymbol{\beta})^2-2\rho(\mathbf{x}'_{i1}\boldsymbol{\beta}+\gamma_0)(\mathbf{x}'_{i2}\boldsymbol{\beta})}{2(1-\rho^2)}}}{\pi\sqrt{1-\rho^2}} < 0.$$

$$\frac{\partial P_1(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\gamma_0,\rho)}{\partial\gamma_0} =$$

$$-\int_{-\infty}^{\mathbf{x}'_{i2}\boldsymbol{\beta}} \frac{e^{-\frac{(\mathbf{x}'_{i1}\boldsymbol{\beta}+\gamma_0)^2+\varepsilon_{i2}^2-2\rho(\mathbf{x}'_{i1}\boldsymbol{\beta}+\gamma_0)\varepsilon_{i2}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}}\,d\varepsilon_{i2} - \int_{-\infty}^{\mathbf{x}'_{i1}\boldsymbol{\beta}} \frac{e^{-\frac{(\mathbf{x}'_{i2}\boldsymbol{\beta}+\gamma_0)^2+\varepsilon_{i1}^2-2\rho(\mathbf{x}'_{i2}\boldsymbol{\beta}+\gamma_0)\varepsilon_{i1}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}}\,d\varepsilon_{i1} < 0.$$

According to the implicit function theorem, the above two inequations imply

$$\frac{d\gamma_0}{d\rho} = -\frac{\frac{\partial P_1(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\gamma_0,\rho)}{\partial\rho}}{\frac{\partial P_1(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\gamma_0,\rho)}{\partial\gamma_0}} < 0 \tag{6}$$

for any given $(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$.

For negative externality $\gamma_0 < 0$, I can similarly obtain

$$\frac{\partial P_1(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\gamma_0,\rho)}{\partial\rho} = -\frac{\partial\Pr(Y_i=0|\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)}{\partial\rho} - \frac{\partial\Pr(Y_i=2|\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)}{\partial\rho} < 0,$$

and

$$\frac{\partial P_1(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i;\boldsymbol{\beta},\gamma_0,\rho)}{\partial\gamma_0} = -\frac{\partial\Pr(Y_i=0|\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)}{\partial\gamma_0} - \frac{\partial\Pr(Y_i=2|\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)}{\partial\gamma_0} < 0.$$

As a result, the implicit function theorem also implies $d\gamma_0/d\rho < 0$ for any given $(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$.

As Altonji et al. (2005) suggest, if the selection of observed characteristics is completely random from the set of all relevant factors, the correlation coefficient of observed characteristics is identical to that of unobserved characteristics,

$$\rho = Cov(\mathbf{x}'_{i1}\boldsymbol{\beta},\mathbf{x}'_{i2}\boldsymbol{\beta}) \tag{7}$$

On the contrary, if all relevant factors are included in the set of observed characteristics, the unobserved characteristics are purely random noises. In the latter case, the correlation among two household members is zero,

$$\rho = 0. \tag{8}$$

The reality is likely to lie between the above two extreme cases. Since I have tried to include the most important variables in the set of regressors $\mathbf{x}_{ij}$, the correlation of the unobserved characteristics is likely to have the same sign as that of observed characteristics, but the magnitude is smaller.[7]

$$0 \le \rho \le Cov(\mathbf{x}'_{i1}\boldsymbol{\beta},\mathbf{x}'_{i2}\boldsymbol{\beta}). \tag{9}$$

Equation (6) shows that there is a negative relationship between the correlation coefficient ρ and the intra-household effect. Therefore, the intra-household effect estimated under Condition (7) is an lower bound of the true value while the effect estimated under Condition (8) is an upper bound.[8]

2.5 Semiparametric Maximum Likelihood Estimator

If consumption 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. Consequently, the usual likelihood can be computed. On the contrary, the exact probabilities of $\{Y_i = 0\}$ and $\{Y_i = 2\}$ are unknown when externality is positive. I use a semiparametric maximum likelihood estimator, extended from Tamer (2003), to obtain the parameters in the demand model. Define the conditional probability of the event $\{Y_i = 0\}$ for observed characteristics $(\mathbf{x}_{i1},\mathbf{x}_{i2},\mathbf{z}_i)$

[6] The computational details are provided in an appendix available from the author.

[7] From the viewpoint of modeling, it is possible to have negative correlation and to use the condition $Cov(\mathbf{x}'_{i1}\boldsymbol{\beta},\mathbf{x}'_{i2}\boldsymbol{\beta}) < \rho < 0$. However, in the estimation, I find the correlation to be positive.

[8] If the joint distribution of unobserved characteristics $(\varepsilon_{i1},\varepsilon_{i2})$ is totally unrestricted, it is bounded by $\max\{\Phi(\varepsilon_{i1})+\Phi(\varepsilon_{i2})-1,0\} \le F(\varepsilon_{i1},\varepsilon_{i2}) \le \min\{\Phi(\varepsilon_{i1}),\Phi(\varepsilon_{i2})\}$, where Φ is the distribution function of standard normal (Hoeffding, 1940). Although these bounds are tight, they are too wide to obtain meaningful parameter estimates.

as

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

When H is known, I can write down the likelihood and the parameters $(\boldsymbol{\beta}, \boldsymbol{\gamma})$ are estimated by maximizing the logarithm of the likelihood function. For a random sample with size N,[9] the logarithm of the likelihood function is

$$\begin{aligned} L(\boldsymbol{\beta}, \boldsymbol{\gamma}, \rho; H) = \frac{1}{N} \sum_i \Big\{ & \mathbf{1}[Y_i = 0] \log(H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)) \\ & + \mathbf{1}[Y_i = 1] \log\left(P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho\right)\right) \\ & + \mathbf{1}[Y_i = 2] \log\Big(1 - H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i) - P_1\left(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho\right)\Big)\Big\} \end{aligned} \tag{10}$$

The unknown function $H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ represents the probability of observing no subscriber in a household in the event of multiple Nash equilibria. From equations (4) and (5), we know $H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ is bounded by the closed interval $[P_0^L(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho), P_0^U(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)]$, but the model cannot predict the exact probability. To overcome this difficulty, Tamer (2003) suggest to approximate the unknown function by a kernel regression of the event $\{Y_i = 0\}$ on $(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$. Since $H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ is bounded by $P_0^L(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$ and $P_0^U(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$, I truncate the result of the kernel regression by the upper and lower bounds and denote the value by $\hat{H}(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i; \boldsymbol{\beta}, \boldsymbol{\gamma}, \rho)$. Replace H in the likelihood (10) by $\hat{H}$. I can obtain a consistent estimate of $(\boldsymbol{\beta}, \boldsymbol{\gamma})$ for any given value of the correlation ρ. The asymptotic variance of the estimate can be computed from the score and Hessian of the log likelihood (10).[10]

I first estimate the model under Condition (7) $\rho = 0$ to obtain an upper bound of intra-household effects. Then, I estimate the model subject to Condition (8) $\rho = Cov(\mathbf{x}_{i1}'\boldsymbol{\beta}, \mathbf{x}_{i2}'\boldsymbol{\beta})$ to find a lower bound of the effect.

Although the model is described under a simultaneous non-cooperative game, it actually includes cooperative game as a special case. If all households can coordinate their consumption decisions, the kernel estimation of $H(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ will converge to $P_0^L(\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{z}_i)$ in probability. Similarly, if individuals make decisions sequentially, then the subsame-prefect equilibrium is also included in the set of Nash equilibria under a simultaneous non-cooperative game.

3 Empirical Results

3.1 Data

I use cross-sectional data from Taiwan, the 2003 Survey of Family Income and Expenditure. 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 kids are unlikely to make their own decisions and they are unlikely to use telephones, young kids are not counted as household members in my empirical work. I define young kids as people who are less than 6 years old. The estimation results do not change much for different definition of young kids. Based on this age criterion, there are 3,489 households with two members.

I only observe the total numbers of cellular phones and landline phones in a household. When the total is zero, obviously neither member subscribes to the phone service. When it is one, only one member in the household choose to subscribe, and the other member does not. When there is more than one phone, I assume that both individuals choose to have one. In my data, 3% of two-member households own more than two cellular phones, and 1% of households have more than two landline phones.

3.2 Demand for Cellular Phone Service

I first estimate the model under the assumption that the correlation of the unobserved characteristics within a household is zero. I will obtain an upper bound estimate of the distribution of intra-household effects. Then, I estimate the lower bound of the distribution by imposing the constraint $Cov(\mathbf{x}_{i1}'\boldsymbol{\beta}, \mathbf{x}_{i2}'\boldsymbol{\beta}) = \rho$.

[9]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 for a random sample in this section.

[10]These two matrices are asymptotically equal for a random sample. However, for the survey data, I need to account for sampling weights in the estimation and the matrices are different.

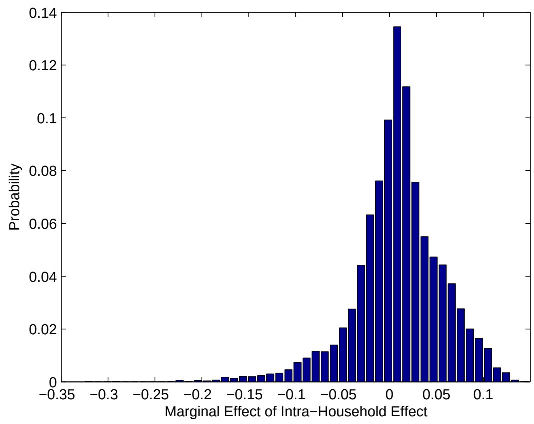

Figure 3: Histogram of the estimated intra-household effects for cellular phone service under zero correlation of unobserved characteristics

3.2.1 Zero Correlation of Unobserved Characteristics

The parameter estimates for the choice of cellular phone service subscription under zero correlation are presented in Table 1. In addition to the household-level variable reported in Table **??**, I also construct six additional household-level characteristics by averaging and differencing individual-level variables: *average age*, *average education years*, *average employment status*, *age difference*, *education difference*, and *income difference*. I report four different specifications. In the first two columns, differences of individual characteristics within a household are not included. In Column (A), I also exclude the regional dummy variables (*Central* and *South*) in the set of observed characteristics. In Column (D), the full set of household-level characteristics is used in the estimation. Some of the covariates are insignificantly different from zero. These covariates are excluded in the estimation for Column (C).

According to likelihood-ratio tests, Column (A) and (B) are both significantly different from Column (D) at the 95% level, suggesting the differences of individual characteristics within a household have significant effects on demand for cellular phone service. On the contrary, no significant difference between the last two columns. I will use the estimation results in Column (C) as the benchmark case.

The magnitude of intra-household effect can be expressed as the marginal effect of one household member's subscription decision on the other member. For member j in household i, the marginal effect is

$$\Pr([\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] + [\mathbf{z}_i'\boldsymbol{\gamma}] > 0) - \Pr([\mathbf{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij}] > 0).$$

Based on the estimated parameters, $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}$, I compute the marginal effect for each individual. Figure 3 shows the distribution of the estimated marginal effects due to the externalities among household members. 63.56% of the estimated effects are positive. On average, the effect increases subscription by 0.93 percentage points. It has standard deviation 4.75 percentage points. When the other household member chooses to subscribe, its average effect is equivalent to the effect caused by a 46,766 TWD (equal to 1,358 USD) increase in individual annual income. Although the average effect is close to zero, the variation of the effect is large among households.

As Figure 3 shows, intra-household effects vary across households. Estimate of the vector γ differ significantly from zero at 5% level for several elements. The effects increase when the number of employed person in a household increases, meaning the network effect of cellular phone usage is stronger when more household members are employed. On the contrary, the effects decrease in the number of young kids and the age difference in a household. People tend to share the usage of a single cellular phone when they have more kids. In addition, the effects are higher for household living in a city. The network effect appear to be stronger in cities. However, there is no significant difference across the regions: North, Central, and South.

3.2.2 Positive Correlation of Unobserved Characteristics

When I assume zero correlation of unobserved factors to obtain Table 1, the correlation coefficient of observed characteristics among individuals in a household is 0.639. This suggests that assuming unobserved characteristics to be uncorrelated among household members might be too restrictive. In this section, I impose the constraint (7) : The correlation coefficient is the same for observed and for unobserved characteristics, $Cov(\mathbf{x}_{i1}'\boldsymbol{\beta}, \mathbf{x}_{i2}'\boldsymbol{\beta}) =$

Table 1: Estimation results for cellular phone service under zero correlation

	(A)		(B)		(C)		(D)	
Characteristics	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ
constant	0.393 (0.135)	-0.404 (0.189)	0.430 (0.146)	-0.416 (0.193)	0.319 (0.126)	0.008 (0.122)	0.401 (0.143)	-0.072 (0.229)
Household Income	0.242 (0.121) [0.061]	0.007 (0.111) [0.002]	0.228 (0.122) [0.058]	0.016 (0.112) [0.004]	0.237 (0.083) [0.061]		0.261 (0.147) [0.067]	0.054 (0.134) [0.014]
Town	-0.049 (0.054) [-0.013]	-0.196 (0.077) [-0.050]	-0.039 (0.051) [-0.010]	-0.193 (0.078) [-0.049]		-0.229 (0.076) [-0.058]	-0.035 (0.048) [-0.009]	-0.199 (0.078) [-0.051]
Rural	-0.078 (0.085) [-0.020]	-0.166 (0.132) [-0.042]	-0.058 (0.073) [-0.015]	-0.165 (0.134) [-0.042]		-0.224 (0.128) [-0.056]	-0.057 (0.071) [-0.015]	-0.170 (0.137) [-0.043]
Central			0.014 (0.052) [0.004]	-0.037 (0.071) [-0.009]	-0.011 (0.043) [-0.003]		0.017 (0.045) [0.004]	-0.045 (0.071) [-0.011]
South			-0.097 (0.034) [-0.024]	0.034 (0.060) [0.008]	-0.093 (0.031) [-0.024]		-0.097 (0.032) [-0.025]	0.027 (0.059) [0.007]
Number of Kids	0.096 (0.077) [0.024]	-0.163 (0.080) [-0.041]	0.090 (0.077) [0.023]	-0.161 (0.080) [-0.040]	0.115 (0.075) [0.030]	-0.240 (0.077) [-0.061]	0.103 (0.080) [0.026]	-0.222 (0.085) [-0.056]
Average Age		0.475 (0.268) [0.120]		0.491 (0.264) [0.123]				0.103 (0.293) [0.026]
Avg. Education		0.193 (0.108) [0.049]		0.182 (0.107) [0.046]		0.160 (0.099) [0.040]		0.169 (0.106) [0.043]
Avg. Employment		0.213 (0.089) [0.054]		0.220 (0.089) [0.055]		0.162 (0.082) [0.041]		0.147 (0.100) [0.037]
Age Difference						-0.747 (0.234) [-0.189]		-0.809 (0.268) [-0.205]
Edu. Difference								0.099 (0.100) [0.025]
Inc. Difference								-0.088 (0.133) [-0.022]
Gender	-0.033 (0.074) [-0.008]		-0.033 (0.073) [-0.008]				-0.053 (0.081) [-0.014]	
Age	-2.853 (0.146) [-0.722]		-2.867 (0.150) [-0.725]		-2.715 (0.147) [-0.697]		-2.792 (0.160) [-0.714]	
Education	0.651 (0.055) [0.165]		0.664 (0.062) [0.168]		0.649 (0.053) [0.167]		0.653 (0.059) [0.167]	
Employment	0.298 (0.054) [0.080]		0.298 (0.054) [0.089]		0.289 (0.045) [0.078]		0.285 (0.048) [0.077]	
Individual Income	0.749 (0.177) [0.190]		0.746 (0.173) [0.189]		0.774 (0.134) [0.199]		0.696 (0.217) [0.178]	
Likelihood	-2539.735		-2537.018		-2533.284		-2531.128	

Notes: Standard errors are in parentheses. Marginal effects are in square brackets, which are computed as average derivatives of the subscription probability except for for dummy variables, whose effects are evaluated for a move from 0 to 1. The sample size is 3489 households or 6978 individuals.

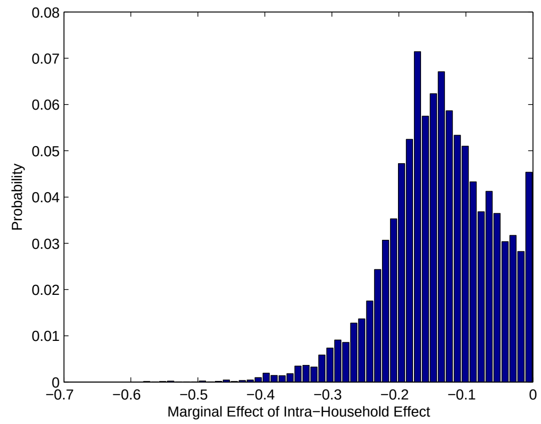

Figure 4: Histogram of the estimated externalities for cellular phone service under positive correlation of unobserved characteristics

$Cov(\varepsilon_{i1}, \varepsilon_{i2}) = \rho$.

The estimated parameters under the constraint on the correlation of unobserved characteristics are presented in Table 2. I estimate the model under the sets of covariates in Column (A) and (C) of Table 1. The distribution of the estimated marginal intra-household effect under specification (C) is illustrated in Figure 4. It has mean -13.92 percentage points and standard deviation 7.87 percentage points. All of the estimated effects are negative.

The estimation under the assumption of random selection of observed characteristics in this subsection gives an lower bound estimate of intra-household effects. When I compare the result with the upper bound estimated zero correlation of unobserved characteristics, the range between these two bounds is $(-0.1392, 0.0093)$. Therefore, I am inconclusive about the sign of average intra-household effect for cellular service demand. Nonetheless, the coefficients of intra-household effect are qualitatively robust except the constant term γ_0. The magnitude of the marginal effects of these coefficients does not change much as well. Ignoring the correlation of unobserved characteristics results in an higher estimate of the constant term for intra-household effect γ_0. The effects on the estimation of other covariates are much smaller in the current study.

As I discussed in Subsection 2.4, the true correlation of unobserved characteristics ρ is likely to lie between the two extreme cases that I have estimated above. When $0 \leq \rho \leq Cov(\mathbf{x}_{i1}'\boldsymbol{\beta}, \mathbf{x}_{i2}'\boldsymbol{\beta})$, the true distribution of consumption externalities lies between the two estimated distributions shown on Figure 3 and Figure 4, respectively. Consequently, it is inconclusive to determine the sign of consumption externality of cellular phone service for most households. Nonetheless, at least 36 44% of them are estimated to be negative.

3.3 Demand for Landline Phone Service

Next, I apply the same estimation approach to the demand for landline phone service. Column (D) in Table 3 use the same set of covariates as Column (D) in Table 1. In Column (E), I exclude covariates which has t-ratio less than 1 in the estimation of Column (D). There is no significant difference between these two specifications. Therefore, the following discussion of estimation result is based on Column since it contents fewer covariates.

The estimations are done under the assumption of zero correlation of unobserved characteristics. As a result, the estimated intra-household effects are upper bounds for landline phone service. The distribution of the estimated marginal intra-household effects is illustrated in Figure 5. Its mean is -55.23 percentage points and standard deviation is 15.25 percentage points. All of the estimated effects are negative. The estimated correlation coefficient of observed characteristics is 0.5401. If the true correlation of unobserved characteristics is also positive, the estimated distribution in Figure 5 must first-order stochastically dominate the true distribution. Consequently, I can conclude that intra-household effect of landline phone service is negative for all households in my sample. On average, an individual's decision to subscribe to landline phone service reduces the other household member's probability of subscription by at least 55.23 percentage points.

The intra-household effect for landline phone demand is higher for household in the North region, but it decrease in household income and average age. Interestingly, similar to the findings in Browning et al. (1994), the differences of characteristics within a household have significant role in the intra-household effect. Difference in education has a negative effect on intra-household effect, while difference in individual income has a positive effect.

Table 2: Parameter estimates under random selection of observed characteristics

	(A)		(C)	
Characteristics	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ
constant	0.737 (0.025)	-1.053 (0.230)	0.665 (0.022)	-0.782 (0.148)
Household Income	0.666 (0.026) [0.160]	-0.290 (0.127) [-0.066]	0.382 (0.038) [0.094]	
Town	-0.080 (0.007) [-0.019]	-0.229 (0.101) [-0.052]		-0.257 (0.087) [-0.059]
Rural	-0.092 (0.010) [-0.022]	-0.243 (0.187) [-0.055]		-0.259 (0.151) [-0.059]
Central			-0.017 (0.008) [-0.004]	
South			-0.112 (0.008) [-0.028]	
Number of Kids	0.218 (0.008) [0.052]	-0.306 (0.053) [-0.070]	0.225 (0.009) [0.055]	-0.328 (0.050) [-0.075]
Average Age		0.228 (0.276) [0.052]		
Average Education		0.411 (0.142) [0.094]		0.250 (0.112) [0.057]
Average Employment		0.395 (0.110) [0.090]		0.296 (0.092) [0.068]
Age Difference				-0.299 (0.263) [-0.068]
Gender	-0.018 (0.011) [-0.004]			
Age	-3.077 (0.025) [-0.741]		-2.944 (0.024) [-0.722]	
Education	0.593 (0.010) [0.143]		0.680 (0.008) [0.167]	
Employment	0.241 (0.010) [0.060]		0.263 (0.010) [0.067]	
Individual Income	0.408 (0.042) [0.098]		0.588 (0.050) [0.144]	
Likelihood	-2575.601		-2569.568	
Correlation ρ	0.7962		0.7259	

Notes: Standard errors are in parentheses. Marginal effects are computed as average derivatives of the subscription probability except for for dummy variables, whose effects are evaluated for a move from 0 to 1. The sample size is 3377 households or 6754 individuals.

Table 3: Estimation results for landline phone service under zero correlation

	(D)		(E)	
Characteristics	$\boldsymbol{\beta}$	γ	$\boldsymbol{\beta}$	γ
constant	-1.281 (0.333)	0.231 (0.389)	-1.177 (0.259)	0.098 (0.264)
Household Income	1.230 (0.285) [0.223]	-0.557 (0.256) [-0.172]	1.322 (0.271) [0.243]	-0.645 (0.229) [-0.199]
Town	-0.096 (0.123) [-0.018]	-0.040 (0.151) [-0.012]		
Rural	0.147 (0.225) [0.025]	-0.074 (0.303) [-0.023]		
Central	0.232 (0.135) [0.040]	-0.386 (0.152) [-0.114]	0.226 (0.123) [0.039]	-0.394 (0.139) [-0.116]
South	0.165 (0.108) [0.029]	-0.345 (0.121) [-0.104]	0.158 (0.100) [0.028]	-0.349 (0.113) [-0.105]
Number of Kids	0.091 (0.105) [0.016]	-0.165 (0.113) [-0.051]		-0.076 (0.047) [-0.024]
Average Age		-2.680 (0.479) [-0.830]		-2.487 (0.337) [-0.769]
Avg. Education		-0.081 (0.184) [-0.025]		
Avg. Employment		-0.020 (0.184) [-0.006]		
Age Difference		0.286 (0.265) [0.089]		0.263 (0.258) [0.081]
Edu. Difference		-0.313 (0.105) [-0.097]		-0.316 (0.105) [-0.098]
Inc. Difference		0.281 (0.112) [0.087]		0.283 (0.108) [0.088]
Gender	0.345 (0.131) [0.062]		0.355 (0.133) [0.065]	
Age	2.234 (0.420) [0.405]		2.034 (0.312) [0.373]	
Education	0.520 (0.159) [0.094]		0.480 (0.075) [0.088]	
Employment	0.053 (0.152) [0.010]			
Individual Income	-0.771 (0.269) [-0.140]		-0.775 (0.274) [-0.142]	
Likelihood	-1347.186		-1349.943	

Notes: Standard errors are in parentheses. Marginal effects are in square brackets, which are computed as average derivatives of the subscription probability except for for dummy variables, whose effects are evaluated for a move from 0 to 1. The sample size is 3489 households or 6978 individuals.

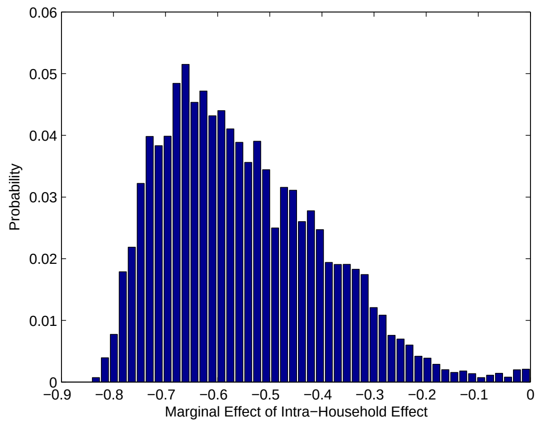

Figure 5: Histogram of the estimated externalities for landline phone service under zero correlation of unobserved characteristics

4 Conclusion

I empirically analyze intra-household effect on the demand for telephone services. Because of the effect, it is possible to have multiple equilibria in a non-cooperative game. Nonetheless, the model is fully identified from household-level data as long as the correlation coefficient of unobserved characteristics is given. Since the correlation cannot be directly identified from the data expect through functional form assumption, I restrict its value to be between zero and the correlation of observed characteristics, based on the idea of selection on observed and unobserved characteristics. This restriction allows me to obtain upper and lower bounds of intra-household effects. I use a semiparametric maximum likelihood estimator to recover the demand for cellular phone service in Taiwan. The sign of intra-household effect of cellular phone service is inconclusive for most households, but the effect of landline phone service is negative for all households.

In the current study, I consider demand for cellular phone service and for landline phone service separately. An interesting extension is to estimate demand for these two services jointly. Another important future work is to include households with more than two individuals. Contrary to the two-member case, the exact probability of any observed event is unknown due to multiple equilibria. The parameters are only partially identified by inequalities.

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計畫成果自評

The methods used in this study is not exactly the same as my original proposal. During the progross of this study, I realized the importance of the correlation on unobserved characteristics in my estimation. Therefore, I turned more attention to this new direction.

The paper has been accepted to several conferences, such as North American Summer Meeting of the Econometric Society and Far Eastern Meeting of the Econometric Society.

The working paper version of my study has been posted on the SSRN website `http://ssrn.com/abstract=991772`. I will submit this paper for publication by the end of October.

出國報告書

會議名稱: 2007 North American Summer Meetings of the Econometric Society

會議時間: 2007.6.21-2007.6.24

會議地點: Duke University, Durham NC, USA

學術交流訪問: 2007.6.26-2007.7.6 Northwestern University, Chicago IL, USA

國立台灣大學經濟學系

助理教授

黃景沂

一、目的

Econometric Society 是國際上最重要的經濟學會之一，每年夏天都會在北美地區舉辦一場經濟學研討會。此次參與的目的，除了發表了一篇文章 Intra-Household Consumption Externalities for the Cellular Phone Service 之外，並且聽取了許多相關領域的最新研究。研討會之後，轉往位在芝加哥的 Northwestern University 訪問，該校爲在產業組織(Industrial Organization)領域方面的研究，在美國居於領導地位。

二、與會過程

在經歷了班機因故延誤與取消、重新劃位等等波折之後，在 2007 年 6 月 20 日傍晚終於順利抵達 Duke University。在完成 check-in 手續，住到該校的宿舍之後，才發現校園內的所有商店都在七點就打烊了，但是校外的商店卻是超出步行範圍。所以當晚只好餓肚子了。(受限於行政院的生活日支費標準，無財力負擔校外的大會指定飯店的住宿費用，否則至少有飯店的餐廳可以吃。)

6 月 21 日開始參加會議，會議在該校商學院 Faqua School of Business 進行。場地的硬體設備相當完善，議程的安排也算是相當流暢。

在接下來的這四天的會議當中，我依序參加了以下的 parallel sessions，聽到了相當多有興趣的文章：

1. Pricing, Advertising, and Entry/Exit
   i. “An Empirical Analysis of the Competitive Effects of the

Delta/Continental/Northwest Codeshare Alliance" by Philip Gayle, Kansas State University

ii. "Targeted Advertising: The Role of Subscriber Characteristics in Media Markets" by Ambarish Chandra, University of British Columbia

iii. "Predatory Advertising: Theory and Evidence in the Pharmaceutical Industry" by Wei Tan, State University of New York at Stony Brook

iv. "Entry and Externality: Hydroelectric Generators in Brazil" by Rodrigo Moita, IBMEC SAO PAULO

2. Search, Matching, and Investment

i. "Diversity and demand externalities: How cheap information can reduce welfare" by Heski Bar-Isaac, NYU

ii. "Too Many Bargainers Spoil The Broth: The Impact of Bargaining on Markets with Price Takers" by John Thanassoulis, Oxford University

iii. "Price Fixing and Non-Price Competition" by Marco Haan, University of Groningen

iv. "Non-Cooperative Foundations of Hedonic Equilibrium" by Michael Peters, University of British Columbia

3. Auction Performance

i. "Strategic Foundations of Prediction Markets and the Efficient Markets Hypothesis" by Ricardo Serrano-Padial, University of California, San Diego

ii. "The eBay Market as Sequential Second Price Auctions---Theory and Experiments" by Joseph Wang, Caltech

iii. "When and How to Dismantle Nuclear Weapons: Auction Design with Externalities" by Jingfeng Lu, National University of Singapore

iv. "Competing Auctions with Endogenous Quantities" by Xianwen Shi, Yale University

4. Partially Identified Models
   i. "Asymptotic behavior of inequality constrained models - with applications to office supply superstores" by Arie Beresteanu, Duke University
   ii. "Weak Identification and Conditional Moment Restrictions" by Sung Jae Jun, the Pennsylvania State University
   iii. "More on Confidence Intervals for Partially Identified Parameters" by Joerg Stoye, New York University
   iv. "A Simple Way to Calculate Confidence Intervals for Partially Identified Parameters" by Tiemen Woutersen, JHU
5. Empirical Studies of Contracting and Asymmetric Information
   i. "Asset Liquidity, Boundaries of the Firm and Financial Contracts: Evidence from Aircraft Leases" by Alessandro Gavazza, Yale University
   ii. "Identifying and Testing Models of Hidden Information and Moral Hazard: An application to Managerial Compensation" by George-Levi Gayle, Carnegie Mellon University
   iii. "Semiparametric Identification of Multidimensional Screening Models" by Heleno Pioner, The University of Chicago
   iv. "Do Lawyers Work for Clients? Using Timing of Dropped Disputes to Estimate Incentive Misalignment" by: Yasutora Watanabe, Northwestern University (KSM)
6. Contract Theory
   i. "Hold-up and Durable Trading Opportunities" by Christopher Wignall, UCSD
   ii. "Rigidity in Nonlinear Pricing under Hidden Investment" by Rui Zhao, University at Albany, SUNY
   iii. "Relative Performance in Bilateral Trade" by Christian Ewerhart,

University of Zurich

iv. "When Should Control Be Shared?" by Paul Milgrom, Stanford University

7. Demand Estimation

i. "Does Buying High Mean Buying Often? Quality Choice and Replacement Cycles for a Vertically Differentiated, Rapidly Improving Durable Good" by Jeffrey Prince, Cornell University

ii. "Deriving the Optimal Pricing Strategy Given the Effect of Dealing Pattern on Consumer Behavior: A Structural Approach" by Priscilla Medeiros, Northwestern University

iii. "Intra-Household Consumption Externalities of Cellular Phone Service" by Ching-I Huang, National Taiwan University

iv. "A Hybrid Discrete Choice Model of Differentiated Product Demand with an Application to Personal Computers" by Minjae Song, University of Rochester

8. Topics in Applied Microeconomics

i. "Air Quality and Neighbors' Effects: Evidence from Survival Analysis" by Mariano Rabassa, University of Illinois Urbana-Champaign

ii. "Do Harsher Punishments Deter Crime? Perceptions and Behavior Around the Age of Criminal Majority" by Randi Hjalmarsson, University of Maryland

iii. "The Impact of Poor Health on Education: New Evidence Using Genetic Markers" by Weili Ding, Queen's University

iv. "Political Price Cycles in Regulated Industries: Theory and Evidence" by Rodrigo Moita, IBMEC SAO PAULO

9. Dynamics and Econometrics in IO

i. "Productivity Dispersion and Plant Selection in the Ready-Mix Concrete

Industry" by Allan Collard-Wexler, New York University

ii. "Nonparametric Identification and Estimation of Finite Mixture Models of Dynamic Discrete Choices" by: Hiroyuki Kasahara, University of Western Ontario

iii. "An Approach to Identification of Marginal Effects in a Correlated Random Effects Model for Panel Data" by Christian Hansen, University of Chicago

10. Auctions, Betting, and Risk Aversion

i. "Rational Expectations at the Racetrack : Testing Expected Utility Theory Using Betting Markets" by Amit Gandhi, University of Chicago

ii. "English Auctions with Resale: An Experimental Study" by Sotirios Georganas, Bonn Graduate School of Economics

iii. "Structural inferences from First-Price Auction data" by Andres Romeu, Universidad de Murcia

iv. "Decision Making Under Risk in Deal or no Deal" by Nicolas de Roos, University of Sydney

11. Labor Economics Topics

i. "The Effects of Short-Term Training Measures on Individual Unemployment Duration in Western Germany" by Stephan Thomsen, ZEW, Mannheim

ii. "Coase Wins After All: No-Fault v.s. Unilateral Divorce Laws and Divorce Rates" by Marjorie McElroy, Duke University

iii. "Did Welfare Reform Improve the Academic Performance of Children in Low-Income Households?" by Lei Zhang, Clemson University

iv. "How Well are Earnings Measured in the Current Population Survey? Bias from Nonresponse, Imputation, and Proxy Respondents" by Barry Hirsch, Trinity University

我個人的文章，則是在 6 月 23 日早上第一場的 session 發表，該場次的四個發表人當中，竟然有三個同樣是與 Northwestern University 有關連的，真是有趣的巧合。在我發表之後，Yasutora Watanabe、Tao-Yi Wang、Hiroshi Ohashi 等人，都給了我相當具體的改進建議。

除此之在，大會也邀請了許多著名學者來發表最新的研究成果。我參加的這些 plenary sessions，聽到以下這些學者的報告: Robert Miller, Kenneth Wilpin, Jonathan Levin, Patrick Bajari, C. Lanier Benkard。他們當中有些人的文章，正好是我最近正在研讀的，能有機會聽到作者親自報告，對於瞭解文章的概念相當有幫助。

在研討會結束，我飛到了芝加哥，到 Northwestern University 進行訪問。主要是跟 Christopher Taber 和 Robert Porter 兩位教授進行討論。我跟 Christopher Taber 有一篇共同的 working paper，受限於地理上的距離跟時差的關係，一直很難進行充分的討論，透過這次的面會面溝通，我們解決了一些文章當中的難題，期望在近期了就能夠將文章完成。Robert Porter 則是針對於一些我目前持續在進行的研究，提供了我很多具體的建議。也給了我將文章投稿至期刊的意見，相信會對於這些文章的投稿有很大的幫助。

The paper I discussed with Professor Christopher Taber is about estimating the peer effects of a universal voucher program in high schools. Such a program will encourage more students to attend private schools. While private schools presumably have better quality, the policy may hurt students staying in public schools after the implementation of the policy. This is because the students who may transfer to private schools are likely to be those with better demographic background. Therefore, the average quality of the students staying in public schools becomes worse. The worsen quality may, in turn, hurts those staying in public schools.

To estimate the potential policy impacts, we estimate a model with school choice and student outcome. In the meetings during my visit, we were trying to figure out the correct formulation to account for the unobservables, both at the individual level and the school level.

As for the meetings with Professor Robert Porter, I was seeking for his comments for several of my working papers, including estimating the demand for cellular phone service using a BLP-style method, estimating the demand with intra-household effects, and a model to explain intra-network discounts in the cellular phone industry. He suggested me a couple of feasible approaches, which I tried to apply to my researches during my visit in Chicago. Moreover, he gives some guidance as for where to submit my papers. Hopefully, his experiences about top economics journals will help me to submit my works to appropriate journals and have them published soon.

In addition, I also invite Professor Robert Porter to visit Taiwan in the future. It seems he is interesting in doing so as long as he has free time. Nonetheless, I am not sure whether the Economics Department in NTU will have sufficient budget for his visiting. Therefore, anything about his visiting is still uncertain.

三、與會心得

這次參加研討會聽到了相當多有趣的文章，這些都是在台灣很難有機會聽到的。與讓自己跟上國際的研究前鋒，實在很有幫助。特別是其中有些文章，正好是我最近正在讀的(例如: Patrick Bajari 對於 multiple Nash equilibria 的賽局模型所提出來的估計方法)，能有機會直接聽到作者親自的報告，對於瞭解文章的概念相當有幫助。

在研討會上遇到了許多昔日在美國念博士班的朋友(Ambarish Chandra、Joerg Stoye、Jeffrey Prince、Arijit Mukherjee、Allan Collard-Wexler、Pablo Guerron-Quintana)，也遇到了不少在其他場合認識的經濟學者。在台灣研究實證產業組織或者是 partially identified model 的人真的相當少。到了這次的會議，感覺上，就像是從一個封閉的小溪游向了大海。也許這些相似領域的朋友，將來可以對與自己的研究，提供很多的幫助。所以，很希望能夠以後還能夠經常在各地的研討會與他們見面。

It is very great to have a chance to visit Northwestern University. After graduating from Northwestern last year, I really miss the overall academic environment there. The professors are nice to discuss academic works with their students. I benefit a lot from the discussions during my visit.

In addition, I find that there are great staffs to support faculty members to do researches in Northwestern University. The professors do not need to worry about bureaucratic stuffs. I think this is really something the NTU needs to learn from top universities in the world. We all spend too much time doing paperworks.

這次獲得國科會與學校相關單位的補助，得以到美國參加研討會，並且前往芝加哥拜訪西北大學的老師，內心實在是非常感激。從美國回到台灣來之後，彷彿是

大腦經歷了一次徹底的充電過程，讓人想要好好地繼續衝刺。然而，回國之後，開始面對報帳的手續，才發現相關的規定實在相當繁瑣，很多事情都跟之前預料的不同。爲了這些報帳的事宜，實在是讓人有些煩躁，無法好好專心從事研究，剛回國的熱情也因此消失了一大半，可以說是相當遺憾的一件事。有時候內心不禁會懷疑當初選擇回到台灣大學工作的決定是否正確。

四、建議事項

Duke University 所在的 Durham, NC，在行政院的生活日支費標準當中，是屬於「其他地區」，因此一天只有 108 美金的生活費。不過大會安排的旅館，住宿一天的費用要 130 美金，超出了我國政府規定的標準。雖然可以住在 Duke University 的宿舍而節省住宿開支，不過絕大多數的與會學者都是住在大會的旅館，只有少數年輕的研究生住在宿舍，因此減少了跟其他較資深學者互動的機會。在此，希望能有管道向行政院建議提高 Durham 的生活日支費。

在會議現場有書商展示最新出版的圖書，並可以當場以優惠價格購買。雖然看到不少對與研究有幫助，值得購買的新書，但是受限於使用國科會經費的相關規定，並沒有辦法當場使用研究經費購買，所以只有自掏腰包購買了其中少數的幾本。個人認爲非常遺憾。將來如果透過行政程序變更經費，再透過台灣的書商購買，不但價格較高，而且也損失了時效性。相較於他國的學者，對於我國的競爭力實在是個無形的損失。在此建議相關單位可以增加研究經費使用的彈性與時效性，以提高研究的生產力。

政府規定出國應該要優先考慮搭乘本國籍的航空公司，實在不是一個很好的措

施。從經濟學的觀點，寡佔的市場往往會造成價格偏高，市場沒有效率。以我這次出國爲例，如果當初選擇國籍航空公司，光是台北到美國來回機票就要四萬六千多元，而且還需要在另外購買美國內陸段的機票，價格將會高出許多，除此之外，因爲航線的限制，所需要的飛行時間也會比較久。爲了要幫國家節省公帑，我還需要另外申請才可以不搭乘國籍的航空公司，實在是浪費時間在 paperwork 之上。除了價格的因素之外，有的國籍航空公司過去的安全紀錄，也真的是令人有點擔心的地方。

五、攜回文件

1. 會議流程手冊
2. 參加書展廠商的最新出版目錄
3. 自費購買的圖書　*Estimating Market Power and Strategies*, by Jeffrey Perloff, Larry S. Karp, and Amos Golan
4. 自費購買的圖書 *Advances in Economics and Econometrics*, edited by Mathias Dewatripont, Lars Peter Hansen, and Stephen J. Turnovsky

Intra-Household Consumption Externalities of Telephone Service

Ching-I Huang*

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Abstract

I propose a game-theoretical model to account for consumption externality of telephone service among household members. I use household-level survey data to estimate individual consumer's choice, accounting for the externality. Although multiple Nash equilibria of subscription decisions may exist in a household, the model parameters are identified from the data for any given correlation coefficient of unobserved characteristics. The value of the correlation of unobserved characteristics is guided by the correlation of observed ones. I investigate the demand in Taiwan by a semiparametric maximum likelihood estimation. The distribution of the estimated externalities of cellular phone service stochastically dominates that of landline phone service. The estimated consumption externalities of landline phone service is negative for all households. However, my estimation is inconclusive about the sign of externalities of cellular phone consumption for most households.

*Department of Economics, National Taiwan University, Taipei, Taiwan. I received helpful comments from Aviv Nevo, Robert Porter, and William Rogerson and seminar participants at National Central University and National Taipei University. The Survey of Family Income and Expenditure was carried out by the Directorate General of Budget, Accounting, and Statistics of the Taiwan Government. The Center for Survey Research of Academia Sinica is responsible for the data distribution. I appreciate the assistance in providing data. Financial supports from the Center for the Study of Industrial Organization at Northwestern University and the National Science Council in Taiwan are gratefully acknowledged. All remaining errors are mine.

1 Introduction

Standard microeconomic theory analyzes consumer behavior based on individual preferences. When more than one person lives in a household, we need to take into account the intra-household allocation of resources and consumption externalities among household members. In this paper, I use a game-theoretical framework to estimate demand for telephone service and analyze the consumption externalities of the subscription decision. There is a rich literature on estimating household demand for telecommunication service. Generally, these studies 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. 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. This assumption is unlikely to be true in most households.[1]

As Browning, Bourguignon, Chaippori, and Lechene (1994) point out, household behavior depends on intra-household interactions unless we impose some restrictive hypotheses. They propose 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 efficient in the bargaining process. Using data on couples with no kids, they find that the allocation of expenditure depends on the relative incomes and 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.

I consider a model of binary subscription choice. When there is only a single person in a household, this model reduces to a standard discrete choice model. When more than one person

[1] Train, McFadden, and Ben-Akiva (1987) and Train, Ben-Akiva, and Atherton (1989) only consider aggregate household income. In the estimation of demand for local telephone service under optional rate plans, Miravete (2002) includes several household-level characteristics. However, his empirical analysis only accounts for household head's individual characteristics, but not other members' characteristics. Many previous researches (Rappoport and Taylor, 1997; Solvason, 1997; Madden and Simpson, 1997; Duffy-Deno, 2001; Rodini, Ward, and Woroch, 2003; Economides, Seim, and Viard, 2006) use similar approach in estimating telephone demand.

lives in a household, the decision would in general depend on the choices of other members. For example, if the husband has a cellular phone, the wife may have a stronger desire to own a cellular phone as well. There are several potential positive spillover effects. First, the husband can be contacted by phone even when he is away from a landline phone. This increases the wife's demand for phone service (the direct network effect). Second, the husband's knowledge of cellular service reduces the wife's information cost of subscription decision (the indirect network effect). Third, when the price of a cellular-to-cellular phone call is lower than a landline-to-cellular phone call[2], the wife pays less for a call from a cellular phone than from a landline phone. Besides, carriers often offer family plans which lowers the subscription fee for a second cellular phone (the price effects) On the other hand, the spillover 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 other person's cellular phone. Whether the net externality is positive or negative is an empirical issue. However, compared to landline phone service, the positive effects are more likely to dominate for cellular service. My empirical findings confirms this conjecture.

In the current paper, I restrict my attention to households with two members under a simultaneous-move non-cooperative game. Each of the two members makes a discrete choice to subscribe for telephone service. My model is similar to entry models in the industrial organization literature, such as Bresnahan and Reiss (1990). However, the externalities between two firms in an entry model are always negative. The entrance of one player reduces the profit of the other player. Their entry decisions must be strategic substitutes. For household consumption behavior, externalities may be positive. When they are positive, the decisions are strategic complements. I do not restrict the sign of externalities in the estimation. The sign can vary across households in my econometric model. Although there is a unique equilibrium for the number of subscribers with negative externalities, such as in an entry model, there are multiple Nash equilibria with positive externalities. Some researches impose rules to select among several

[2] This is the case when cellular carriers offers intra-network discounts.

Nash equilibria. In a recent paper, Bajari, Hong, and Ryan (2007) suggest a simulation-based method to estimate the selection rule. In Tamer (2003), the selection among multiple equilibria is determined by a semiparametric estimation of the data. The econometric model in this paper is an extension of Tamer (2003). I show that the parameters in the demand model can be pointwise identified as long as the correlation of unobserved characteristics is given.

The unobserved characteristics of individuals within a household are likely to be positively correlated. Although the correlation can be formally identified without an instrumental variable, the identification is only based on the functional form specification, not from the data. In this paper I impose the idea developed in Altonji, Elder, and Taber (2005) to identify the within-household correlation of unobserved characteristics from the correlation of observed ones. The true value of the correlation depends on the data structure. On the one extreme, if the set of observed characteristics includes all relevant ones, the within-household correlation of unobserved characteristics is zero. On the other extreme, if observed characteristics are randomly chosen from all possible factors, the correlation of these characteristics is identical to the correlation of the unobserved ones. Consequently, I require the correlation of unobserved characteristics to be bounded by these two extreme cases.

I apply the econometric model to study the demand for cellular and lineline phone services in Taiwan. By using the 2003 Family Income and Expenditure Survey, I estimate consumption externality for each household. When I restrict the correlation of unobserved individual characteristics to zero, estimated externalities of cellular phone service are positive for 69.87% of households and have a positive mean. Nevertheless, this is upper bounds of externalities. I obtain lower bounds by requiring the correlation of unobserved characteristics equal to that of observed ones. The estimated externalities are then negative for all households. Therefore, the analysis is inconclusive about the sign of consumption externality of cellular phone service for most households. On the contrary, the upper bounds of consumption externalities of landline phone service are negative for all household. Consequently, landline phone service is a public good in a household. The decision to subscribe to a landline phone service is a strategic substitute within a household. As a result, when we analyze household consumption, it is important to account for the interactions within a household. Furthermore, the distribution of the upper-bound estimates of the externalities of landline phone service is first-order stochastically dominated by the distribution of the lower-bound estimates of the externalities of cellular phone service. Negative spillover effects are relatively more important for landline phone service than for cellular phone service.

Another important contribution of this paper is to estimate the effects of individual demographics on telephone demand. Previous researches only include household characteristics in the estimation. As a result, it is difficult to identify the effect of some demographic variables such as gender. My estimation finds that income and education have positive effects on both cellular and landline phone services. Employment and younger age (< 40) are important factors for higher demand of cellular phone service. Females on average have stronger demand for landline phone service.

In the next section, I show the econometric model and discuss the difficulties regrading demand estimation. In Section 3, I present my estimation results on the consumption of telephone service in Taiwan. Concludes are in the final section.

2 Econometric Model

The presence of externalities within a household implies that consumption depends on the decision of other household members. I consider a static discrete response model which is an extension of the probit model. In this paper, I restrict my attention to households with two members and show that, conditional on a given correlation coefficient of unobserved characteristics, the model parameters are fully identified despite the existence of multiple Nash equilibria in a noncooperative game between two household members.

2.1 Discrete Response Model

For household i, there are two members $j \in \{1, 2\}$. Let the binary variable $y_{ij} \in \{0, 1\}$ denote the subscription decision of individual j in household i. $y_{ij} = 1$ if and only if the individual subscribes to a telephone network. The demand is assumed to be

$$y_{ij} = 1 \quad \Leftrightarrow \quad [x'_{ij}\beta + \varepsilon_{ij}] + y_{i(3-j)}[x'_i\gamma] > 0, \tag{1}$$

where $(3 - j)$ is the index for the other member in the household. Let $Y_i = y_{i1} + y_{i2}$ be the total number of subscribers in the household.

The terms in the first bracket of equation (1) represents the own effect of the consumption choice. The vector x_{ij} is the set of observed characteristics, and ε_{ij} represents characteristics unobserved to the econometrician. The observed characteristics x_{ij} includes variables both at the household and the individual levels. It also includes a constant term. Therefore, a nonempty common subset of x_{ij} exists for the two members in a household. Denote these household-level characteristics by x_i. At least one of the covariates in x_{ij} must be at the individual level for the identification of the model (i.e. $x_i \subsetneqq x_{ij}$).

The term in the second bracket of equation (1), $x'_i\gamma$, is the consumption externality due to the other household member's choice. It is reciprocal between these two members. I normalize the externality to be zero if the other member do not subscribe. The externality is assumed to be completely captured by observed characteristics x_i.[3] My model reduces to the probit model if the externality vanishes ($\gamma = 0$).

The unobserved characteristics $(\varepsilon_{i1}, \varepsilon_{i2})$ are assumed to be jointly normally distributed,

[3]In theory, I can extend the model to include a unobserved part of consumption externality so that externality can expressed as $x'_i\gamma + \eta_i$. But the extended model is computationally intensive. When I use a simplified version of the extended model to gauge the importance of unobserved externality, the variance of unobserved externality η_i is estimated to be only 0.002 of the variance of unobserved characteristics ε_{ij}. Therefore, I decide to ignore the effect of unobserved externality η_i for the rest of the paper.

independently across households.

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

The variance of ε_{ij} is normalized to one.

The unobserved characteristics of individuals within a household are likely to be positively correlated. The correlation coefficient ρ in (2) is identified only through functional form specification, not from observed data. It cannot be accurately estimated. As a result, I apply the idea developed in Altonji et al. (2005) and use the correlation of observed characteristics to provide information about the correlation of unobserved ones. See Section 2.4 below for more details about assumptions on the unobserved factor.

2.2 Nash Equilibria

Consider a simultaneous-move non-cooperative game.[4] This is similar to the incomplete model discussed in Tamer (2003). Figure 1 shows the set of equilibria for positive externality ($x_i'\gamma > 0$) conditional on observed characteristics (x_{i1}, x_{i2}, η_i) and unobserved characteristics $(\varepsilon_{i1}, \varepsilon_{i2})$. There are multiple Nash equilibria when $(\varepsilon_{i1}, \varepsilon_{i2}) \in (-x_{i1}'\beta - x_i'\gamma, -x_{i1}'\beta) \times (-x_{i2}'\beta - x_i'\gamma, -x_{i2}'\beta)$. Both $(y_{i1}, y_{i2}) = (0, 0)$ and $(y_{i1}, y_{i2}) = (1, 1)$ are equilibria in this region. Nonetheless, the model predicts the exact probability for $(y_{i1}, y_{i2}) = (0, 1)$ and $(y_{i1}, y_{i2}) = (1, 0)$. The probability of the event $(0, 0)$ is bounded by

$$\Pr\left(\{\varepsilon_{i1} < -x_{i1}'\beta - x_i'\gamma,\ \varepsilon_{i2} < -x_{i2}'\beta\} \cup \{\varepsilon_{i1} < -x_{i1}'\beta,\ \varepsilon_{i2} < -x_{i2}'\beta - x_i'\gamma\} | x_i'\gamma > 0\right)$$

and

$$\Pr(\varepsilon_{i1} < -x_{i1}'\beta,\ \varepsilon_{i2} < -x_{i2}'\beta | x_i'\gamma > 0).$$

[4] The set of Nash equilibria under a cooperative game is included in the set of Nash equilibria under a non-cooperative game. Consequently, the results under a cooperative game can be viewed as imposing an equilibrium selection rule on the results under a non-cooperative game.

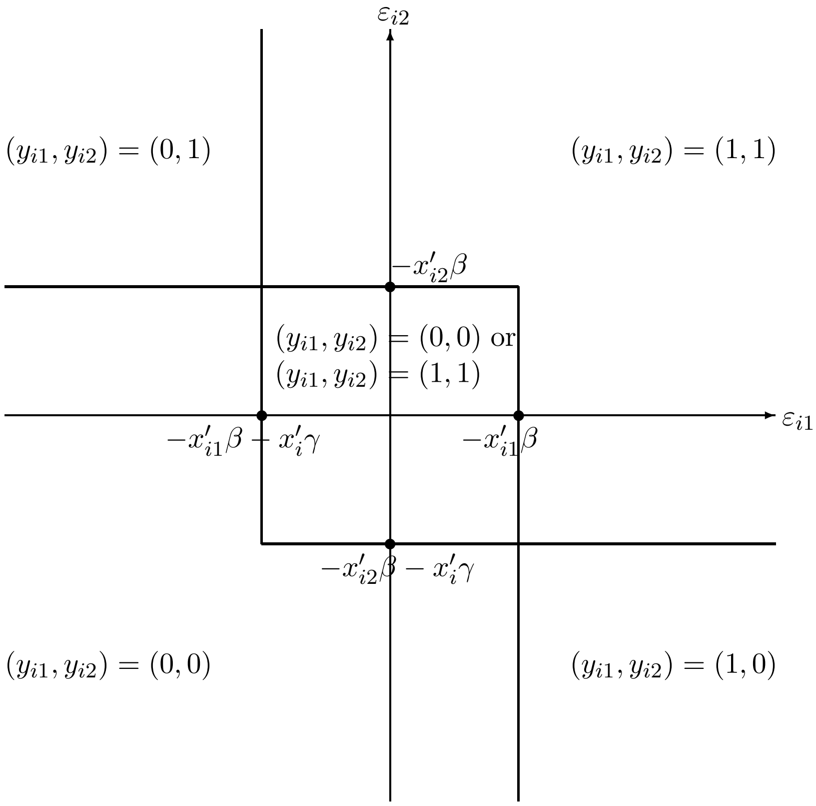

Figure 1: Simultaneous-move non-cooperative game for positive externality

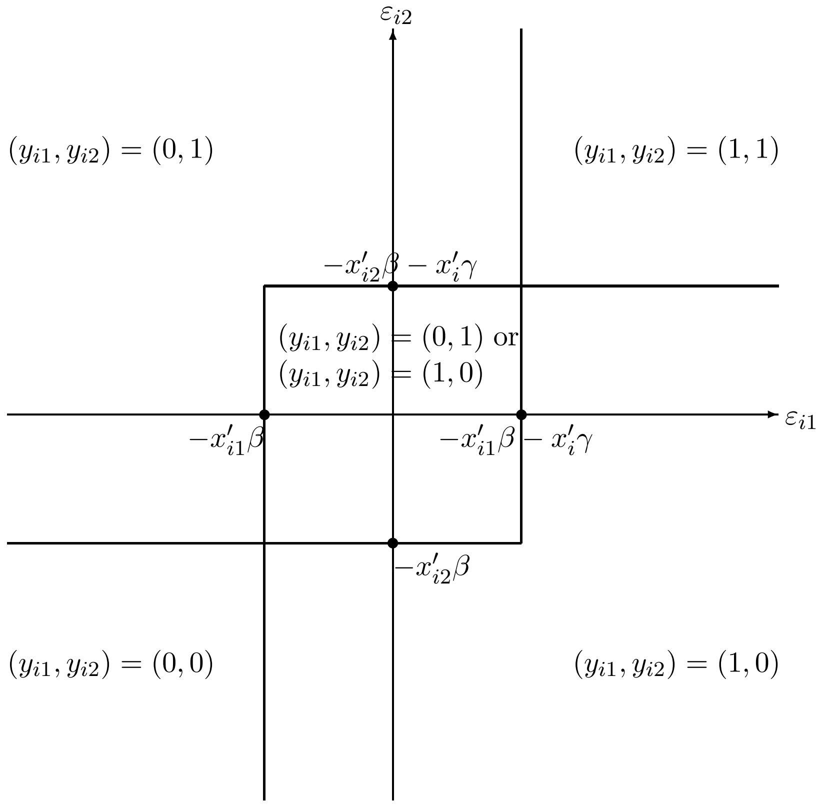

Figure 2: Simultaneous-move noncooperative game for negative externality

On the other hand, when the externality is negative ($x_i'\gamma < 0$), there are multiple equilibria of $(0,1)$ and $(1,0)$ if $(\varepsilon_{i1}, \varepsilon_{i2}) \in (-x_{i1}'\beta, -x_{i1}'\beta - x_i'\gamma) \times (-x_{i2}'\beta, -x_{i2}'\beta - x_i'\gamma)$. (See Figure 2.) The model gives the exact probabilities of $(y_{i1}, y_{i2}) = (0,0)$ and $(y_{i1}, y_{i2}) = (1,1)$.

Regardless the sign of consumption externality, the exact probability of observing one subscriber in a household ($Y_i = y_{i1} + y_{i2} = 1$) for given observed characteristics (x_{i1}, x_{i2}) can be obtain from the model.

$$\begin{aligned}
&\Pr(Y_i = 1 | x_{i1}, x_{i2}; \beta, \gamma) = \\
&\qquad \Pr\left(\varepsilon_{i1} < -x_{i1}'\beta - x_i'\gamma,\ \varepsilon_{i2} > -x_{i2}'\beta\right) + \Pr\left(\varepsilon_{i1} > -x_{i1}'\beta,\ \varepsilon_{i2} < -x_{i2}'\beta - x_i'\gamma\right) \\
&\qquad\quad - \mathbf{1}\{x_i'\gamma < 0\} \Pr\left(-x_{i1}'\beta < \varepsilon_{i1} < -x_{i1}'\beta - x_i'\gamma, -x_{i2}'\beta < \varepsilon_{i2} < -x_{i2}'\beta - x_i'\gamma\right), \quad (3)
\end{aligned}$$

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

However, the exact probabilities of no subscriber ($Y_i = 0$) and two subscribers ($Y_i = 2$) in a household are unknown when consumption externality is positive because we do not know how individuals choose among multiple Nash equilibria. Without loss of generality, we only need to focus on the probability $\Pr(Y_i = 0|x_{i1}, x_{i2})$ because $\Pr(Y_i = 2|x_{i1}, x_{i2})$ can be obtained from $1 - \Pr(Y_i = 0|x_{i1}, x_{i2}) - \Pr(Y_i = 1|x_{i1}, x_{i2})$. The probability of no subscriber in a household is bounded in an interval. The upper bound occurs when individuals always fail to coordinate their decisions in the event of multiple Nash equilibria.

$$P_U\left(x_{i1}, x_{i2}; \beta, \gamma\right) \equiv \Pr(\varepsilon_{i1} < -x_{i1}'\beta,\ \varepsilon_{i2} < -x_{i2}'\beta). \tag{4}$$

The lower bound is achieved when individuals can perfectly coordinate.

$$\begin{aligned} P_L\left(x_{i1}, x_{i2}; \beta, \gamma\right) \equiv{}& \Pr(\varepsilon_{i1} < -x_{i1}'\beta,\ \varepsilon_{i2} < -x_{i2}'\beta) \\ &- \mathbf{1}\{x_i'\gamma > 0\} \Pr(-x_{i1}'\beta - x_i'\gamma < \varepsilon_{i1} < -x_{i1}'\beta,\ -x_{i2}'\beta - x_2'\gamma < \varepsilon_{i2} < -x_{i2}'\beta). \end{aligned} \tag{5}$$

2.3 Identification

Although there are multiple Nash equilibrium in my econometric model, the parameters can be pointwise identified as long as the correlation coefficient of the unobserved characteristics ρ in (2) is known. My model is similar to Tamer (2003), which is identified when we have data on the individual decisions $\{(y_{i1}, y_{i2})\}$. However, the data set that I use only reports the total consumption in a household ($Y_i = y_{i1} + y_{i2}$), not individual choices. The following theorem is an extension of Theorem 1 in Tamer (2003).

Theorem 1. *Suppose that there exists a regressor of individual characteristics (x_{i1k}, x_{i2k}) with $x_{i1k} \neq x_{i2k}, \beta_k \neq 0$ and such that the conditional distribution of $x_{i1k}|x_{-i1k}$ has an everywhere positive Lebesgue density where $x_{-i1k} = (x_{i11}, \ldots, x_{i1,k-1}, x_{i1,k+1}, \ldots, x_{i1K})$. Then the parameter vectors, β and γ, are identified for any given covariance matrix of unobserved characteristics* *if both the matrices x_{i1} and x_{i2} have full column rank.*

Proof. In equation (3), I have shown that the exact probabilities of $Y_i = 1$ can be obtained for any given observed characteristics (x_{i1}, x_{i2}).

Without loss of generality, assume $\beta_k > 0$. Let b be different from β and r be different from γ. Suppose $b_k > 0$. As x_{i1k} goes to minus infinity for given x_{-i1k}, both $x_{i1k}\beta_k$ and $x_{i1k}b_k$ go to minus infinity. Because x_{i2} has full rank, there exists x_{i2}^* such that $x_{i2}^{*\prime}\beta \neq x_{i2}^{*\prime}b$. Consequently, as $x_{-i1k} \to -\infty$,

$$\begin{aligned}\Pr\left(Y_i = 1|x_{i1}, x_{i2}^*; \beta, \gamma\right) &\simeq \Pr\left(\varepsilon_{i2} > -x_{i2}^{*\prime}\beta\right) \\ &\neq \Pr\left(\varepsilon_{i2} > -x_{i2}^{*\prime}b\right) \simeq \Pr\left(Y_i = 1|x_{i1}, x_{i2}^*; b, \gamma\right).\end{aligned}$$

This implies the vector β is identified.

Now, let x_{i1k} go to positive infinity. Both $x_{i1k}\beta_k$ and $x_{i1k}b_k$ go to positive infinity. Because x_{i2} has full rank, there exists x_{i2}^{**} such that $x_{i2}^{**\prime}\beta + x_i^{**\prime}\gamma \neq x_{i2}^{**\prime}b + x_i^{**\prime}r$ where x_i^{**} is the projection of x_{i2}^{**} onto the space spanned by household-level characteristics. As $x_{-i1k} \to +\infty$, I have

$$\begin{aligned}\Pr\left(Y_i = 1|x_{i1}, x_{i2}^{**}; \beta, \gamma\right) &\simeq \Pr\left(\varepsilon_{i2} < -x_{i2}^{**\prime}\beta - x_i^{**\prime}\gamma\right) \\ &\neq \Pr\left(\varepsilon_{i2} < -x_{i2}^{**\prime}b - x_i^{**\prime}r\right) \simeq \Pr\left(Y_i = 1|x_{i1}, x_{i2}^{**}; b, r\right).\end{aligned}$$

Therefore, I can identify the sum $(\beta_l + \gamma_l)$ for each element γ_l in the vector γ. This implies γ is identified.

For $b_k < 0$, $x_{i1}'\beta$ increases in x_{i1k}, but $x_{i1}'b$ decreases. Consequently, there exists x_{i1k}^* such that $x_{i1}^{*\prime}\beta = x_{i1}^{*\prime}b$. Similar to the above arguments, I can show that β and γ are both identified. □

2.4 Unobserved Characteristics

As I mentioned at the beginning of this section, the observed data cannot truly identify the covariance matrix of the unobserved characteristics (2). In fact, the correlation coefficient ρ can not be separately identified from the mean of consumption externality. To demonstrate this, consider the relationship between ρ and γ_0, where γ_0 is the constant term in the linear expression of consumption externality $x_i'\gamma$. For positive externality,[5]

$$\begin{aligned}
&\Pr(Y_i = 1|x_{i1}, x_{i2}) \\
=&\Pr(x_{i1}'\beta + x_i'\gamma + \varepsilon_{i1} < 0, x_{i2}'\beta + \varepsilon_{i2} > 0) + \Pr(x_{i1}'\beta + \varepsilon_{i1} > 0, x_{i2}'\beta + x_i'\gamma + \varepsilon_{i2} < 0) \\
=&\int_{-\infty}^{-x_{i1}'\beta - x_i'\gamma} \int_{-\infty}^{x_{i2}'\beta} \frac{e^{-\frac{\varepsilon_{i1}^2+\varepsilon_{i2}^2+2\rho_I\varepsilon_{i1}\varepsilon_{i2}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}}\, d\varepsilon_{i2}\, d\varepsilon_{i1} + \int_{-\infty}^{x_{i1}'\beta} \int_{-\infty}^{-x_{i2}'\beta - x_i'\gamma} \frac{e^{-\frac{\varepsilon_{i1}^2+\varepsilon_{i2}^2+2\rho\varepsilon_{i1}\varepsilon_{i2}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}}\, d\varepsilon_{i2}\, d\varepsilon_{i1}.
\end{aligned}$$

Consider the partial derivatives with respect to ρ and γ_0, respectively.[6]

$$\frac{\partial \Pr(Y_i = 1|x_{i1}, x_{i2})}{\partial \rho} = -2\frac{\rho(1 - \Pr(Y_i = 1|x_{i1}, x_{i2}))}{1-\rho^2} - 2\frac{e^{-\frac{(x_{i1}'\beta + x_i'\gamma)^2 + (x_{i2}'\beta)^2 - 2\rho(x_{i1}'\beta + x_i'\gamma)(x_{i2}'\beta)}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}},$$

which is negative for $\rho \geq 0$.

$$\begin{aligned}
&\frac{\partial \Pr(Y_i = 1|x_{i1}, x_{i2})}{\partial \gamma_0} = \\
&-\int_{-\infty}^{x_{i2}'\beta} \frac{e^{-\frac{(x_{i1}'\beta + x_i'\gamma)^2 + \varepsilon_{i2}^2 - 2\rho(x_{i1}'\beta + x_i'\gamma)\varepsilon_{i2}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}}\, d\varepsilon_{i2} - \int_{-\infty}^{x_{i1}'\beta} \frac{e^{-\frac{(x_{i2}'\beta + x_i'\gamma)^2 + \varepsilon_{i1}^2 - 2\rho(x_{i2}'\beta + x_i'\gamma)\varepsilon_{i1}}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}}\, d\varepsilon_{i1} < 0.
\end{aligned}$$

According to the implicit function theorem, the above two inequations imply

$$\frac{dv}{d\rho} = -\frac{\frac{\partial \Pr(Y_i=1|x_{i1},x_{i2})}{\partial \rho}}{\frac{\partial \Pr(Y_i=1|x_{i1},x_{i2})}{\partial \gamma_0}} < 0 \tag{6}$$

[5] The result for negative externality is similar.

[6] The computational details are provided in an appendix available from the author.

for any given value of $\Pr(Y_i = 1|x_{i1}, x_{i2})$ when $\rho \geq 0$. Consequently, the correlation coefficient of the unobserved characteristics ρ cannot be separately identified from the externality v.

As Altonji et al. (2005) suggest, if the selection of observed characteristics is completely random from the set of all relevant factors, the correlation coefficient of observed characteristics is identical to that of unobserved characteristics,

$$\rho = Cov(x'_{i1}\beta, x'_{i2}\beta) \tag{7}$$

On the contrary, if all relevant factors are included in the set of observed characteristics, the unobserved characteristics are purely random noises. In the latter case, the correlation among two household members is zero. The reality is likely to lie between the above two extreme cases. Since I have tried to include the most important variables in the set of regressors x_{ij}, the correlation of the unobserved characteristics is likely to be positive but less than that of observed characteristics.

$$0 \leq \rho \leq Cov(x'_{i1}\beta, x'_{i2}\beta). \tag{8}$$

Equation (6) shows the derivative of externality on the correlation coefficient is negative. Therefore, the consumption externality estimated under the assumption $Cov(x'_{i1}\beta, x'_{i2}\beta) = \rho$ is an lower bound of the true value while the externalities estimated under zero correlation $Cov(x_{i1}, x_{i2}) = 0$ is an upper bound.

2.5 Semiparametric Maximum Likelihood Estimator

If consumption externality 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. Consequently, the usual likelihood can be computed. On the contrary, the exact probabilities of $\{Y_i = 0\}$ and $\{Y_i = 2\}$ are unknown when externality is positive. I use a semiparametric maximum likelihood estimator, extended from Tamer (2003), to obtain the parameters in the demand model. Define the conditional probability of the event $\{Y_i = 0\}$ for observed characteristics (x_{i1}, x_{i2}) as

$$H(x_{i1}, x_{i2}) = \Pr(Y_i = 0|x_{i1}, x_{i2}).$$

When H is known, I can write down the likelihood and the parameters (β, γ) are estimated by maximizing the logarithm of the likelihood function. For a random sample with size N,[7] the logarithm of the likelihood function is

$$\begin{aligned} L(\beta, \gamma; H) = \frac{1}{N}\sum_i \Big\{ & \mathbf{1}[Y_i = 0] \log(H(x_{i1}, x_{i2})) \\ & + \mathbf{1}[Y_i = 1] \log\left(\Pr[Y_i = 1|x_{i1}, x_{i2}; \beta, \gamma]\right) \\ & + \mathbf{1}[Y_i = 2] \log\Big(1 - H(x_{i1}, x_{i2}) - \Pr[Y_i = 1|x_{i1}, x_{i2}; \beta, \gamma]\Big)\Big\} \end{aligned} \tag{9}$$

The unknown function $H(x_{i1}, x_{i2})$ represents the probability of observing no subscriber in a household in the event of multiple Nash equilibria. From equations (4) and (5), we know $H(x_{i1}, x_{i2})$ is bounded by the closed interval $[P_L(x_{i1}, x_{i2}), P_U(x_{i1}, x_{i2})]$, but the model cannot predict the exact probability. To overcome this difficulty, Tamer (2003) suggest to approximate the unknown function by a kernel regression of the event $\{Y_i = 0\}$ on (x_{i1}, x_{i2}).[8] Since $H(x_{i1}, x_{i2})$ is bounded by $[P_L(x_{i1}, x_{i2}), P_U(x_{i1}, x_{i2})]$, I truncate the result of the kernel regression by the upper and lower bounds and denote the value by $\hat{H}(x_{i1}, x_{i2})$. Replace H in the

[7] 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 for a random sample in this section.

[8] I use Gaussian kernel to estimate $H(x_{i1}, x_{i2})$.

$$\hat{H}(x_{i1}, x_{i2}) = \frac{\frac{1}{N}\sum_{i'} \mathbf{1}[Y_{i'} = 0]\phi\left(\frac{1}{B}\rho[(x_{i1}, x_{i2}), (x_{i'1}, x_{i'2})]\right)}{\frac{1}{N}\sum_{i'} \phi\left(\frac{1}{B}\rho[(x_{i1}, x_{i2}), (x_{i'1}, x_{i'2})]\right)},$$

where ϕ is the density function of a standard normal distribution, and the metric ρ is defined as

$$\rho[(x_{i1}, x_{i2}), (x_{i'1}, x_{i'2})] \equiv \sqrt{\frac{1}{2K}\sum_{j=1}^{2}\sum_{k=1}^{K} \frac{(x_{ijk} - x_{i'jk})^2}{Var(x_{\cdot jk})}}.$$

A bandwidth $B = 0.3$ is used for the following results. The parameter estimates are robust to changes in the bandwidth B.

likelihood (9) by $\hat{H}$. I can obtain a consistent estimate of (β, γ). The asymptotic variance of the estimate can be computed from the score and Hessian of the log likelihood (9).[9]

Although the model is described under a simultaneous non-cooperative game, it actually includes cooperative game as a special case. If all households can coordinate their consumption decisions, the kernel estimation of $H(x_{i1}, x_{i2})$ will converge to $P_L(x_{i1}, x_{i2})$ in probability. Similarly, if individuals make decisions sequentially, then the subsame-prefect equilibrium is also included in the set of Nash equilibria under a simultaneous non-cooperative game.

3 Empirical Results

3.1 Data

I use cross-sectional data from Taiwan, the 2003 Survey of Family Income and Expenditure. 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 kids are unlikely to make their own decisions and they are unlikely to use telephones, young kids are not counted as household members in my empirical work. I define young kids as people who are less than 6 years old. The estimation results do not change much for different definition of young kids. Based on this age criterion, there are 3,489 households with two members.

Descriptive statistics are presented in Table 1. The first two columns are 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 includes variables at the individual level. Incomes are measured in Taiwan dollars (TWD).[10] Note that household income is more than twice of individual income in the subsample because part of the household

[9]These two matrices are asymptotically equal for a random sample. However, for the survey data, I need to account for sampling weights in the estimation and the matrices are different.

[10]The average exchange rate between US dollars and Taiwan dollars in 2003 is 1 USD = 34.42 TWD.

Table 1: Descriptive statistics

Variable	Subsample Mean	Subsample Std. Dev.	Entire Sample Mean	Entire Sample Std. Dev.	Description
Cell Phone	1.0715	0.8761	1.8593	1.3239	No. of cell phones
Land Phone	1.1077	0.3958	1.2086	0.5328	No. of landline phones
Income_H	0.7889	0.6028	1.0648	0.7398	Annual HH income (10^6 TWD)
City	0.7929	0.4053	0.8071	0.3946	HH in a city
Town	0.1683	0.3742	0.1627	0.3691	HH in a town
Rural	0.0388	0.1930	0.0302	0.1713	HH in rural area
North	0.4440	0.4969	0.4721	0.4992	HH in North region
Central	0.2231	0.4164	0.2278	0.4194	HH in Cental region
South	0.3329	0.4713	0.3001	0.4583	HH in South region
NoKids	0.2697	0.5971	0.2170	0.5304	No. of young kids
HH_size	2.0000	0.0000	3.3107	1.4896	No. of HH members
Gender	0.5105	0.4999	0.5008	0.5000	Female = 1
Age1	0.2633	0.4405	0.2344	0.4236	$25 < \text{Age} \leq 40$
Age2	0.3764	0.4845	0.3400	0.4737	$40 < \text{Age} \leq 65$
Age3	0.2951	0.4561	0.1171	0.3215	$\text{Age} > 65$
Education	8.8405	4.7766	9.6248	4.2360	Years of Education
Student	0.0321	0.1762	0.2256	0.4180	Student = 1
Employment	0.4778	0.4995	0.4655	0.4988	Employed = 1
Income_I	0.3676	0.4634	0.3011	0.4489	Individual Income (10^6 TWD)
sample size	3489		13681		

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

Table 2: Distribution of the number of telephones among households

	Percentage	
Number	Cellular Phone	Landline Phone
0	30.57	1.88
1	35.32	86.56
2	31.32	10.56
3	2.02	0.92
4	0.73	0.08
5	0.05	0.00

Notes: The sample size is 3489 households. Percentages are computed according to the sampling weights.

income cannot be attributed to either member. The average age in the subsample is considerably older than the entire population. This is reasonable because families with at least one teenager and their parents are excluded in the subsample. Households in the subsample also tends to have lower total income and fewer cellular phones since the their sizes are smaller on average. Besides, households in the subsample are modestly more likely to live in the South region.[11]

I only observe the total numbers of cellular phones and landline phones in a household. Table 2 summarizes the distributions of the number of telephones among households with two members. When the total is zero, obviously neither member subscribes to the phone service. When it is one, only one member in the household choose to subscribe, and the other member does not. When there is more than one phone, I assume that both individuals choose to have one. In my data, 3% of two-member households own more than two cellular phones, and 1% of these households have more than two landline phones.

3.2 Demand for Cellular Phone Service

I first estimate the model under the assumption that the correlation of the unobserved characteristics within a household is zero. I will obtain a estimated distribution of the consumption

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

externalities in the economy. Then, I will allow the correlation to be positive under the constraint $Cov(x_{i1}'\beta, x_{i2}'\beta) = \rho$ and obtain another estimated distribution. The true distribution lies between these two estimated ones.

3.2.1 Zero Correlation of Unobserved Characteristics

The parameter estimates for the choice of cellular phone service subscription under zero correlation are presented in Table 3.

The magnitude of consumption externality can be expressed as the marginal effect of one household member's subscription decision on the other member. For member j in household i, the marginal effect is

$$\Pr(x_{ij}'\beta + x_i'\gamma + \varepsilon_{ij} > 0) - \Pr(x_{ij}'\beta + \varepsilon_{ij} > 0).$$

Based on the estimated parameters, $\hat{\beta}$ and $\hat{\gamma}$, I compute the marginal effect for each individual. Figure 3 shows the distribution of the estimated marginal effects due to the externalities among household members. 69.87% of the estimated externalities are positive. On average, the externality increases subscription by 2.02 percentage points. It has standard deviation 3.86 percentage points. When the other household member chooses to subscribe, its average effect is equivalent to the effect caused by a 118,824 TWD (equal to 3,452 USD) increase in individual annual income. Most observed variables do no affect consumption externality at 5% significance level. Nonetheless, the number of children has a significantly negative effect. An additional child in a household reduces the marginal effect of consumption externality by 5.03 percentage points. In households with young kids, the two members are more likely to share their usage of a single cellular phone.

The estimation result also shows the effects affecting cellular phone subscription conditional on the choice of the other member. Most household-level characteristics have insignificant effects after controlling for externality, but living in the South region reduces the demand by 2.78 percentage points significantly. Individual income is much more important than household

Table 3: Estimation results for cellular phone service under zero correlation

	β		γ	
Variable	Estimate	Marginal Effect	Estimate	Marginal Effect
constant	-0.7376 (0.1703)		-0.1064 (0.1513)	
Income_H	0.1349 (0.1126)	0.0336	0.1016 (0.0985)	0.0255
City	0.0562 (0.1051)	0.0140	0.1847 (0.1373)	0.0468
Town	0.0407 (0.1090)	0.0101	-0.0004 (0.1472)	-0.0001
Central	-0.0097 (0.0415)	-0.0024	-0.0197 (0.0685)	-0.0049
South	-0.1115 (0.0322)	-0.0278	0.0475 (0.0583)	0.0119
NoKids	0.0661 (0.0722)	0.0164	-0.2005 (0.0727)	-0.0503
Gender	-0.0406 (0.0644)	-0.0101		
Age1	0.2180 (0.1216)	0.0565		
Age2	-0.4267 (0.1186)	-0.1057		
Age3	-1.1933 (0.1177)	-0.3345		
Education	0.0837 (0.0045)	0.0208		
Student	-0.2753 (0.1477)	-0.0679		
Employment	0.3444 (0.0495)	0.0913		
Income_I	0.6838 (0.1558)	0.1701		
Likelihood	-2534.300			

Notes: Standard errors are in parentheses. Marginal effects are computed as average derivatives of the subscription probability except for for dummy variables, whose effects are evaluated for a move from 0 to 1. The sample size is 3489 households or 6978 individuals.

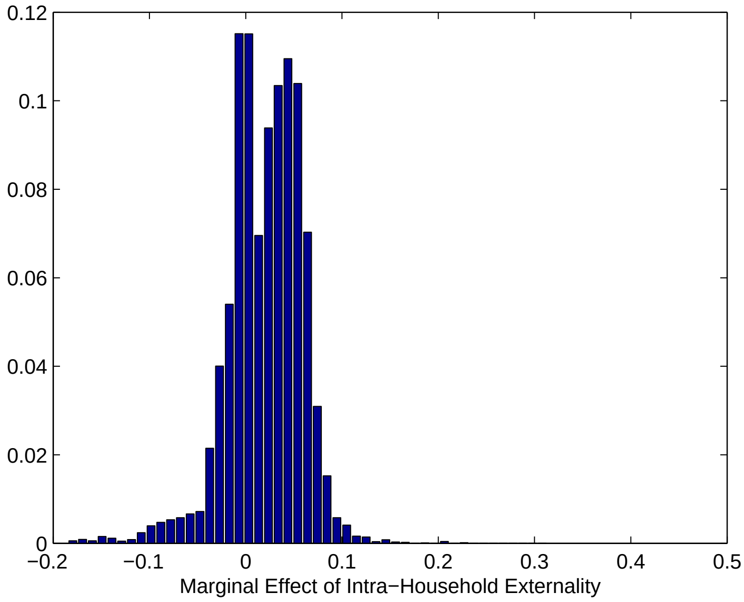

Figure 3: Histogram of the estimated externalities for cellular phone service under zero correlation of unobserved characteristics

income. Household income has a positive but insignificant effect. Increasing annual household income by 1 million TWD raises the demand by 3.36 percentage points. On the contrary, individual income has a stronger and significant effect. A 1 million TWD increase in individual income increases the probability of subscription by 17.01 percentage points. In addition, older people have significantly lower demand for cellular phone service. An additional year of education significantly increase demand by 2.08 percentage points. Employment also have a positive effect by increasing the probability of subscription by 9.13 percentage points.

Table 4 and Table 5 show the penetration rate of cellular service across regions and across urbanization levels. The penetration rate is higher in the North region and in cities. Nevertheless, according to Table 3, living in the South region is the only significant factor affecting demand. There is little evidence showing that network effects among households in the same geographic area result in higher demand.

Table 4: Cellular phone ownership by region

	North	Central	South
Cellular Phone per Household	2.0422	1.7941	1.6212
	(0.0169)	(0.0254)	(0.0184)
Cellular Phone per Person	0.5739	0.4892	0.4806
	(0.0043)	(0.0060)	(0.0048)
Sample Size	5989	2854	4838

Notes: Standard errors for the sampling process are in parentheses.

Table 5: Cellular phone ownership by urbanization level

	City	Town	Rural Area
Cellular Phone per Household	1.9522	1.5314	1.1450
	(0.0125)	(0.0280)	(0.0573)
Cellular Phone per Person	0.5557	0.4198	0.3489
	(0.0032)	(0.0068)	(0.0153)
Sample Size	11018	2223	440

Notes: Standard errors for the sampling process are in parentheses.

3.2.2 Positive Correlation of Unobserved Characteristics

When I assume zero correlation of unobserved factors to obtain Table 3, the correlation coefficient of observed characteristics among individuals in a household is 0.602. This suggests that assuming unobserved characteristics to be uncorrelated among household members seems too restrictive. In this section, I impose the constraint (7): The correlation coefficient is the same for observed and for unobserved characteristics, $Cov(x'_{i1}\beta, x'_{i2}\beta) = Cov(\varepsilon_{i1}, \varepsilon_{i2}) = \rho$.

The estimated parameters under the constraint on the correlation of unobserved characteristics are presented in Table 6. Because it is computationally intensive to obtain the maximum likelihood estimator, I do not include all the covariates used in the previous estimation.

The distribution of the estimated marginal effect of the externalities for cellular phone service is illustrated in Figure 4. It has mean -12.03 percentage points and standard deviation 6.32 percentage points. All of the estimated externalities are negative.

There are two important findings when we compare the estimation results with and with-

Table 6: Parameter estimates under correlated unobserved characteristics

	β		γ	
Variable	Estimate	Marginal Effect	Estimate	Marginal Effect
constant	-0.5207 (0.0165)		-0.6242 (0.2152)	
Income_H	0.4544 (0.0244)	0.1085	-0.0911 (0.1014)	-0.0218
City	0.1038 (0.0107)	0.0250	0.2192 (0.1929)	0.0527
Town	0.0441 (0.0091)	0.0105	0.0282 (0.2039)	0.0067
Central	-0.0097 (0.0083)	-0.0023	-0.0274 (0.0853)	-0.0065
South	-0.1201 (0.0077)	-0.0288	0.0375 (0.0714)	0.0089
Age2	-0.5714 (0.0122)	-0.1311		
Age3	-1.4094 (0.0117)	-0.3972		
Education	0.0885 (0.0008)	0.0211		
Student	-0.4023 (0.0294)	-0.0960		
Employment	0.3971 (0.0098)	0.1006		
Income_I	0.3992 (0.0479)	0.0954		
Likelihood		-2574.190		

Notes: Standard errors are in parentheses. Marginal effects are computed as average derivatives of the subscription probability except for for dummy variables, whose effects are evaluated for a move from 0 to 1. The sample size is 3377 households or 6754 individuals.

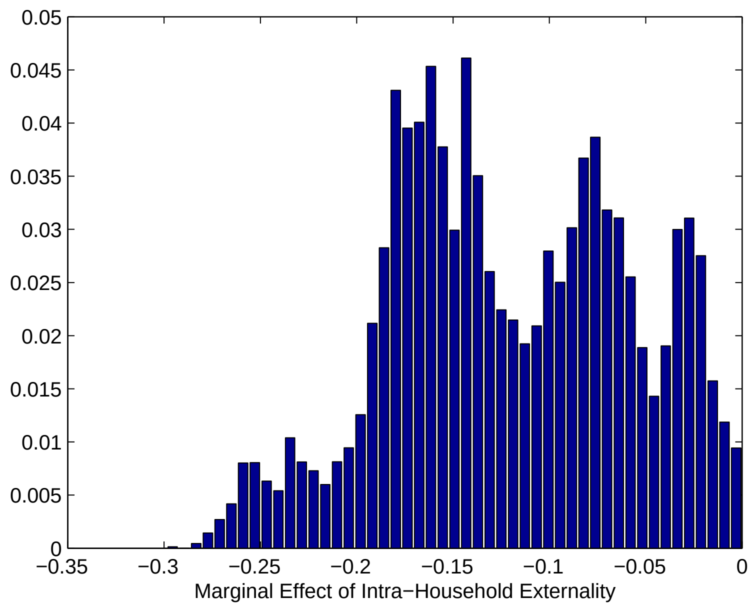

Figure 4: Histogram of the estimated externalities for cellular phone service under positive correlation of unobserved characteristics

out within-household correlation of unobserved factors. First, the externalities estimated under positive correlation are, on average, much smaller than the externalities estimated estimated under no correlation. Second, except the constant term of consumption externality (γ_0), the parameter estimates are robust to the two different specifications on the correlation of unobserved characteristics. Imposing the constraint on the correlation of unobserved characteristics drastically change the sign of the estimated externalities for most households. The seemingly positive consumption externality may be actually resulted from unobserved common factors within a household. The distribution of the estimated externalities under zero correlation (Figure 3) first-order stochastically dominates the the distribution estimated under the assumption of equal selection on observed and unobserved characteristics (Figure 4).

Despite the change in the constant term of consumption externality, the estimated marginal effect of most other parameters does not change much. The parameter estimates under positive correlation are generally more accurate as standard errors become smaller for several parameters.

The effect of household income becomes significant and its magnitude is slightly larger than the effect of individual income.

As I discussed in Section 2.4, the true correlation of unobserved characteristics ρ is likely to lie between the two extreme cases that I estimated above. When $0 \leq \rho \leq Cov(x'_{i1}\beta, x'_{i2}\beta)$, the true distribution of consumption externalities lies between the two estimated distributions shown on Figure 3 and Figure 4, respectively. Consequently, it is inconclusive to determine the sign of consumption externality of cellular phone service for most households. Nonetheless, at least 30.13% of them are estimated to be negative.

3.3 Demand for Landline Phone Service

Next, I apply the same estimation approach to the demand for landline phone service. Table 7 shows the estimation result under the assumption of zero within-household correlation of unobserved characteristics.

The distribution of estimated marginal effects of the externalities for landline phone service is illustrated in Figure 5. Its mean is -55.67 percentage points and standard deviation is 10.91 percentage points. All of the estimated externalities are negative. As I indicated in Section 2.4, the externalities estimated under zero correlation are upper bounds. Therefore, as long as the true correlation is positive, the estimated distribution in Figure 5 must first-order stochastically dominate the true distribution. Consequently, I can conclude the consumption externality of landline phone service is negative for all households in my sample. On average, an individual's decision to subscribe to landline phone service reduces the other household member's probability of subscription by at least 55.67 percentage points.

The consumption externality is higher for household in the North region. An individual in the North region is more likely to subscriber to landline phone service when the other household member does so than individuals in the other two regions by roughly 11%.

Besides, demand for landline phone service is affected by several individual characteristics significantly. Individual income has a positive effect. Increasing annual income by 1 million

Table 7: Estimation results for landline phone service under zero correlation

	β		γ	
Variable	Estimate	Marginal Effect	Estimate	Marginal Effect
constant	0.3347		-1.6031	
	(0.3256)		(0.3070)	
Income_H	0.2777	0.0536	-0.1928	-0.0618
	(0.2221)		(0.2086)	
City	-0.2598	-0.0465	0.1869	0.0587
	(0.2536)		(0.3018)	
Town	-0.2850	-0.0605	0.0597	0.0193
	(0.2519)		(0.3086)	
Central	0.2433	0.0438	-0.4179	-0.1264
	(0.1287)		(0.1452)	
South	0.1527	0.0288	-0.3470	-0.1084
	(0.1004)		(0.1131)	
NoKids	-0.0616	-0.0119	0.1188	0.0381
	(0.0953)		(0.0955)	
Gender	0.4388	0.0857		
	(0.1533)			
Age1	-0.0571	-0.0112		
	(0.2030)			
Age2	0.1754	0.0331		
	(0.2003)			
Age3	0.0382	0.0073		
	(0.2086)			
Education	0.0394	0.0076		
	(0.0074)			
Student	0.2139	0.0371		
	(0.2590)			
Employment	-0.0878	-0.0171		
	(0.0836)			
Income_I	0.7480	0.1445		
	(0.1754)			
Likelihood	-1381.288			

Notes: Standard errors are in parentheses. Marginal effects are computed as average derivatives of the subscription probability except for for dummy variables, whose effects are evaluated for a move from 0 to 1. The sample size is 3489 households or 6978 individuals.

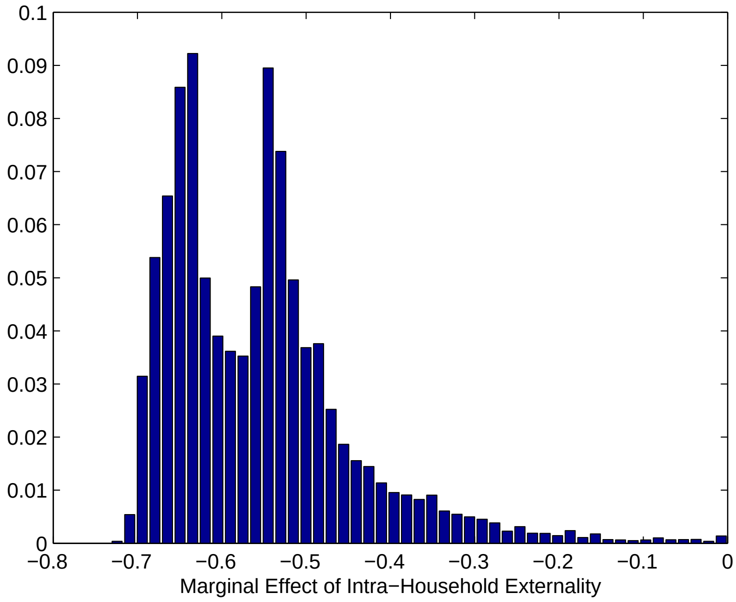

Figure 5: Histogram of the estimated externalities for landline phone service under zero correlation of unobserved characteristics

TWD raises the demand by 14.45 percentage points. The probability of subscription for women is higher than that for men by 8.57 percentage points. An additional school year increase the demand by 0.76 percentage points. Different from the demand for cellular phone service, age does not play a significant role in the demand for landline phone service.[12]

Compare the externality of cellular phone service with that of landline phone service. The former one is clearly more positive than the latter one on average. The average effect due to the externality of cellular phone is estimated to be in the interval $(-12.03\%, 2.02\%)$. The upper bound of the average effect due to externality of landline phone is -55.67%. Moreover, as Figure 6 shows, the distribution of the lower bound of the former one first-order stochastically dominates the distribution of the upper bound of the latter one. This finding is consistent with

[12]Compare with previous studies on the estimation of demand for landline phone service in the U.S., Miravete (2002) finds household income and household head's education have negative effects in two cities in Kentucky in 1986. Economides et al. (2006) also find a negative effect of income on the demand in New York State in the period 1999 – 2003.

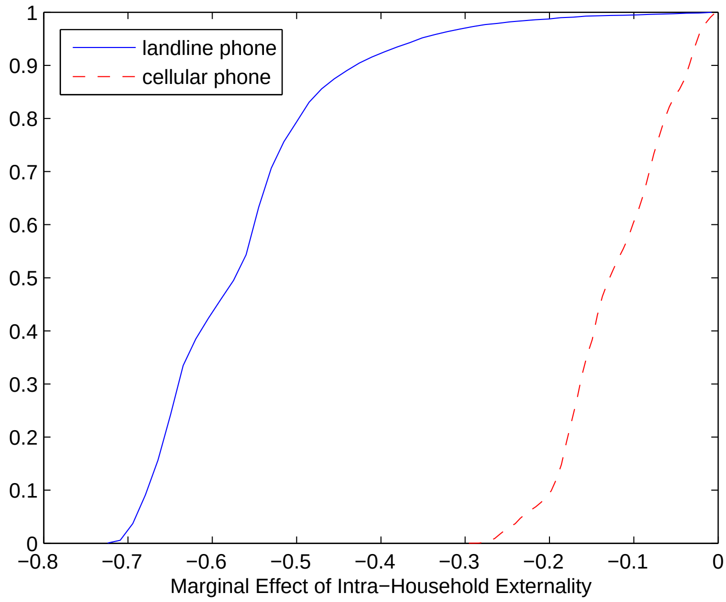

Figure 6: The cumulative distribution of the lower bound of externalities of cellular phone service and the distribution of upper bound of externalities of landline phone service

intuition since it is less common for people to share a cellular phone with their family. On the other hand, it is easier to be a free rider on landline phones. Landline phones are more like public goods in a household than cellular phones.

4 Conclusion

I estimate the distribution of within-household consumption externalities. Because of the externalities, it is possible to have multiple equilibria in a non-cooperative game. Nonetheless, the model is fully identified from household-level data conditional on any given correlation coefficient of unobserved characteristics. Since the correlation cannot be directly identified from the data expect through functional form assumption, I restrict its value to be between zero and the correlation of observed characteristics, based on the idea of selection on observed and unobserved characteristics. This restriction allows me to obtain upper and lower bounds of consumption externalities. I use a semiparametric maximum likelihood estimator to recover the demand for cellular phone service in Taiwan. The sign of consumption externality of cellular phone service is inconclusive for most households, but consumption externality of landline phone service is negative for all households.

The game-theoretical model also allows me to estimate the effect of individual characteristics on telephone demand. Income and education increase demand for both phone services. Employment status and age affect the demand for cellular phone service, while gender affects the demand for landline phone service.

In the current paper, I consider demand for cellular phone service and for landline phone service separately. An interesting extension is to estimate demand for these two services jointly. Another important future work is to include households with more than two individuals. Contrary to the two-member case, the exact probability of any observed event is unknown due to multiple equilibria. The parameters are only partially identified by inequalities.

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