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Etudes et Documents n° 14, CERDI, 2013

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Etudes et Documents n° 14

July 2013

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Directeur de la publication : Patrick Plane
Directeur de la rédaction : Catherine Araujo Bonjean
Responsable d'édition : Annie Cohade
ISSN : 2114 - 7957

Abstract

This study aims at testing the theoretical issue according to which multinomial logit (MNL) would give lower performance than a mixed multinomial logit (MMNL) in the presence of heterogeneity. To do so, we construct two samples of patients surveyed within the same regions in rural China, but of an interval of 18 years, with a difference in preference heterogeneity due to income growth and population aging. With the 1989-1993 sample, both models have predicted price effects; however with the 2004-2006 sample, unlike MMNL, MNL failed to predict price effect. The explanation is that the impact of price on choice became more heterogeneous in the later than the former sample, thus heterogeneity makes a difference between MNL and MMNL. The absence of meaningful divergences of distance effects between the two models can also be explained by the evolution of heterogeneity in distance preferences over the period. The coefficients of price and distances with MMNL are higher than with MNL, indicating stronger price and distance effects in MMNL estimations. Another advantage of MMNL is the possibility to measure the extent of heterogeneity. The findings suggest caution when interpreting estimation results with MNL if heterogeneity is deemed important.

Keywords: healthcare choice, preference heterogeneity, multinomial and mixed logit model, Chinese rural households.

JEL Classification: D1, C5, I1.

1. Introduction

McFadden's choice model (McFadden 1974) is well known as conditional logit, and more generally, as multinomial logit (MNL) model. More recently developed is the mixed multinomial logit (MMNL) model, which methodologically demonstrated having a lot of advantages over MNL (see the literature reviewed on this topic in Hensher *et al.* 1999, Louviere *et al.* 2000, Train 2003, Jones and Hensher 2004, and Hensher *et al.* 2005).

According to the researchers favoring new approaches, the standard MNL model could not incorporate heterogeneity properly. In that model, the accent is on the mean impact of observed variables and all unobserved heterogeneity is classified in error terms. A MNL model has the advantage of simplicity but is limited by its inherent property of "independence from irrelevant alternatives" (IIA). This property is based on the convenient but simplistic assumption of "independent and identically distributed" (IID). If a researcher omits the existence of unobserved heterogeneity, it will produce inconsistent parameter estimation.

MMNL provides a flexible framework to incorporating both observed and unobserved factors that influence the provider choice decision. MMNL allows the parameter associated with each observed variable to vary randomly across individuals, and their variance reflects the unobserved individual-specific heterogeneity. This method decomposes the mean and standard deviation of one or more random parameters to reveal sources of systematic taste heterogeneity.

An empirical issue would be to verify in the presence of preference heterogeneity whether MMNL provides superior performance over MNL. As shown in the subsequent review of literature, a lot of comparisons have been performed in the fields of transportation, marketing, accounting, and others. Healthcare demand provides a promising case for testing since there exists general preference heterogeneity. Several works have applied MMNL in healthcare demand (Harris and Keane, 1999; Borah, 2006; Canaviri, 2007; Hole, 2008; and Qian *et al.*, 2009); nevertheless, the empirical comparisons between MNL and MNL are lacking.

This study is guided by the following idea. If the theoretical inference on the comparison between MNL and MMNL is right, then when constructing two samples with different degrees of preference heterogeneity, MMNL will provide superior performance over MNL with one sample having a higher degree of heterogeneity than another one.

From the CHNS data source, we constructed two samples surveyed within the same regions but for two periods: a 1989-1993 sample with 1,457 rural patients, and a 2004-2006 sample with 2,594 rural patients in the same villages in nine Chinese provinces. With an interval of 18 years, we focused on two most important factors that could lead patients' choice heterogeneity to vary: general income growth and population aging.

First, with the average per capita income at constant prices and household assets increased two to three fold between the two samples, an evident effect would be that the choices become more heterogeneous among the patients because budget constraints becomes softer. People will tend to make their choices more on the functions of such factors as quality and reputation of the healthcare providers. They will be less sensitive to the price of healthcare and price effect heterogeneity will reflect increasing effects of some unobservable factors.

Second, with the average age of the sample individuals rising from 44 to 56 and with the share of aged people over 65 doubled, patients with less favorable health conditions would be less sensitive to price and their choices would be more affected by other factors. For instance, when patients are aged, the unobservable relationship between the aged parents and the younger members within the household may lead to very different choices.

The arguments that income growth and population aging lead choice heterogeneity to vary are based on some theoretical and logical inferences that can be tested. One advantage of MMNL, and also one of the reasons for which it is used, is its ability to measure the extent of choice heterogeneity. Thus, the estimation results will demonstrate whether heterogeneity changes over the two periods.

We focus on two healthcare provider characteristics that may primarily determine the patient's choice: price and distance. The importance of distance is that it conditions the healthcare choice of Chinese rural villagers: first because of population aging, and second because of the backward transportation conditions in rural areas. With the presence of a larger degree of heterogeneity of price effects in the 2004-2006 sample vs. the 1989-1993 sample, we apply both MNL and MMNL models with exactly the same random and non-random variables. If in the second period, the performance of MNL is lower than in the first period while that of MMNL remains stable, we conclude that in the presence of preference heterogeneity, MMNL provides superior performance over MNL. Otherwise, we will reject this conclusion.

This study is organized as follows. Section 2 reviews the literature on the comparison between MNL and MMNL in relation to heterogeneity, and introduces how the income growth and population aging affected healthcare demand heterogeneity between the 1989-

1993 and 2004-2006 samples. Section 3 presents the data and methodology, and section 4 analyzes the results of estimations. Section 5 presents the study conclusions.

2. Review of Literature on Demand Heterogeneity and an Extension to Rural China

2.1. MNL and MMNL in Presence of Heterogeneity

This section draws on the work of, among others, Bhat (2000B), Baltas and Doyle (2001), Christiadi and Cushing (2007) and Train (2009).

MNL and MMNL are based on random utility (RU) models developed to describe choice among mutually exclusive discrete alternatives. With Uij to represent the utility of individual i choosing state j, j will be chosen if and only if Uij > Uil for $j \neq l$. As researchers do not know the individual's true utility, Uij consists of a predicted utility:

$$\boldsymbol{U_{ij} = V_{ij} + \varepsilon_{ij}(1)} \quad \textbf{(1)}$$

Uij is composed of an observable component based on observed attributes affecting choice, and an unobserved random component, εij, depending upon the heterogeneity in tastes, measurement errors, and functional misspecification. Since εij is unknown, the final outcome is predicted in terms of probability.

$$\boldsymbol{P_{ij} = P\left(\left(\varepsilon_{il} - \varepsilon_{ij}\right) < \left(V_{ij} - V_{il}\right)\right) for\ all\ j \neq l.} \quad \textbf{(2)}$$

Solving equation (2) requires imposing a probability density function on $\boldsymbol{\varepsilon ij}$. MNL restricts all εij to be IID, meaning that error terms are assumed to have the same distribution, with the same mean and variance and also to be uncorrelated across and within individuals. Only under this condition can the probability of individual i choosing destination j be solved as a closed-form expression of:

$$\boldsymbol{P_{ij} = \frac{e^{V_{ij}}}{\sum_j e^{V^{ij}}} = \frac{e^{\alpha Z_{ij}}}{\sum_j e^{\alpha Z_{ij}}}} \quad \textbf{(3)}$$

Zij and α represent all the observed factors and their parameters obtained from the model. With εij being IID, equation (3) imposes the IIA assumption. To prove this, consider the probability that individual i chooses state j versus state l. The probability ratio of choosing between j and l is:

$$\boldsymbol{\frac{P_{ij}}{P_{il}} = \frac{\sum_j e^{\alpha Z_{ij}}}{\sum_j e^{\alpha Z_{ij}}} \Big/ \frac{e^{\alpha Z_{ij}}}{e^{\alpha Z_{il}}} = \frac{e^{\alpha Z_{ij}}}{e^{\alpha Z_{il}}}} \quad \textbf{(4)}$$

The probability ratio depends only on the attributes of j and l, and not on the attributes of other destinations.

As the MNL model is based on IID, and hence on the IIA assumption, its failure to deal with heterogeneity can result in inferior model specification, spurious test results and invalid conclusions (Louviere *et al.* 2000; Train 2003). Heterogeneity caused by alternative attributes and individual preference can branch into three major topics: 1) unobserved heterogeneity in alternatives; 2) taste variation of the deciders; and 3) heterogeneous choice sets (Baltas and Doyle, 2001).

First, unobserved heterogeneity in alternatives violates the assumption of independence because it implies the existence of common factors affecting the utilities of the various alternatives and causes correlation in the unobserved portion of utility across alternatives.

Second, when unobserved heterogeneity exits in the form of taste variations in an attribute, the assumption of identically distributed and of response homogeneity will be violated. For example, without unobservable individual heterogeneity, the patients classify their preference order on the function of prices of the alternatives. But this could not be the case if there is taste heterogeneity. For example, one patient may abnormally underestimate a clinic if he was ever badly received there. With this kind of heterogeneity being large, the IID and IIA assumptions are no longer held.

Finally, IIA implies that the ratio of the probabilities of any two alternatives is independent from the choice set. Unobserved heterogeneity in a choice set violates IIA because with different patients, their choice sets will no longer be the same and do not follow the same preference order. For instance, there are two healthcare providers and the probability of going to each provider is 50%. Now assume that a third clinic opens up. If the IIA holds, the probability of going to each provider must now be one third. But if the patient's belief in Chinese or Western medicines is an unknown heterogeneity, and the new clinic is Chinese medicine-oriented, some patients believing more in traditional Chinese medicine will have a different preference order than those believing more in Western medicine. Thus, IIA is violated.

MMNL is similar to a MNL except that it allows parameter estimates to vary across individuals. Through attributing each respondent a random term, taste variations, unobserved heterogeneity in alternatives and unobserved heterogeneous choice sets are allowed. For example, if attributing each patient a specific coefficient of price for each alternative, it reflects both their taste and also their sensibility in unobserved heterogeneity in alternatives and their unobserved heterogeneous choice set.

Consider the following utility function:

$$\boldsymbol{U_{ij} = \alpha_i Z_{ij} + \varepsilon_{ij} = (a + \xi_i) Z_{ij} + \varepsilon_{ij}} \quad \textbf{(5)}$$

In the first equality, α now differs across individuals. Like MNL, MMNL assumes that the error terms, εij, are IID with extreme value. However, it relaxes the restriction that α is the same for each individual, allowing it to be stochastic instead.

The second equality in (5) expresses another way to look at MMNL. a_i is perceived as its mean, a, and a deviation around the mean, ξ, which differs across individuals. With non-zero error components $\xi_i Z_{ij}$, utility becomes correlated across alternatives, which relaxes the IIA assumption. Each individual now has his/her own value of α; thus MMNL incorporates taste variations across individuals.

2.2. Empirical Comparison

As shown, MNL is based on the assumption of IID that imposes IIA. In the presence of large-scale heterogeneity, MMNL that relaxes IID will lead to marked improvement in estimations relating to MNL. MMNL leads to gaining generality, but the estimation simplicity that characterizes MNL is lost. Thus when MNL is not biased, MNL is preferred. An empirical issue is to compare the performances between them. Most comparisons are on the willingness-to-pay (WTP) for various attributes of the alternatives in which mean coefficients are transformed in terms of WTP.

Some works concluded that random unobserved heterogeneity in the marginal utilities does not bias the MNL estimates. Horowitz (1980) found that the WTP estimated by MNL on the simulated datasets for all amounts of heterogeneity in marginal utilities was almost identical to the design value. He concluded that the ratio of the coefficients is unbiased when one does not control for heterogeneity in the marginal utilities. The results in Van den Berg *et al.* (2010) suggest that random unobserved heterogeneity in marginal utilities does not in itself bias the MNL estimates. However, if two heterogeneous marginal utilities are correlated, then the WTP's from MNL may be biased. Carlsson (2003) provided results indicating that with the two models, there are no conflicting signs and the magnitudes of the coefficients are very close, with just a few exceptions. Dahlberg and Eklöf (2003) also reached similar conclusions.

Bhat (1998, 2000A) found that WTP's for all attributes are higher with MMNL than with MNL, indicating that MNL underestimates the WTP's. Revelt and Train (1998) showed significant differences in WTP's for some attributes while no differences for others. Other researchers provided evidence that WTP's are higher for some attributes but lower for others in MMNL than in MNL. Van den Berg et al. (2009) found that MNL underestimates the WTP for travel time compared with mixed logit, but overestimates the WTP's for the other attributes. Train (1998) showed that the WTP's are larger with MMNL than with MNL. However, the WTP's from his MMNL with correlated marginal utilities are smaller than those from MNL. He concluded that there is probably no general answer to whether or not MNL gives correct estimates when heterogeneity is present.

Only a few works have reached the conclusion that in the presence of heterogeneity, MNL models lead to estimating failures. Persson's (2002) finding suggested that model choice indeed has implications for the results since the welfare estimates from the two models differ quite remarkably. There are conflicting signs between MNL and MMNL. MNL provides signs of price elasticity and WTP that contradict the fundamental laws implied in welfare economics.

But in general, most research studies have noted that MMNL provides improved overall goodness of fit, indicating that the explanatory power of the MMNL is considerably greater than with MNL.

2.3. Heterogeneity in Healthcare Choices in Rural China

According to theoretical inferences, with the existence of unobserved heterogeneity, the MNL method, when lying on unrealistic assumptions, tends to bias estimations. In what follows, this study shows that Chinese rural health demand choice is a promising case for comparing the performance of MNL and MMNL in the presence of heterogeneity. Relating the middle of 2000 to the end of 1980, due to general increases of income and age, healthcare choice in rural China is expected to become much more heterogeneous. A two-period comparison between MNL and MMNL may help to answer whether in the presence of large-scale heterogeneity, MMNL has stronger performance than MNL.

Several sources of unobservable heterogeneity can potentially exist in healthcare provider choice in rural China. On the side of unobserved healthcare provider attributes, there are at least two: 1) factors in non-price competition and 2) transport accessibility. Across the same type of healthcare provider (like a county hospital), their equipment levels, the quality and the experience of their professional staffs are different. In particular the perception of their non-price competition by the local population is an unobserved variable for research. For transport accessibility, given that distance is an observed variable, the accessibility that varies with specific transportation conditions across the same type of healthcare provider is an unobserved factor. A farther distance is counterbalanced by, for instance, more frequent public transport.

On the side of taste variations of rural patients, there can be several sources. First, there are differences in judgments on the efficiency of Chinese medicine across patients. Those believing more in Chinese medicine tend more to choose small healthcare providers, while those distrusting Chinese medicine tend toward larger healthcare providers. Second, there are differences in patients' perceptions about the efficiency of the same type of health providers due to their past experiences with certain healthcare providers. Third, there are differences in the connections with personal relation networks. Given that in China a personal relation network is so determinant, the extent of this network with the same type of healthcare provider is different across patients. Other things being equal, one patient prefers a township health center over a county hospital just because he has a relative working in the first one. Fourth, there is subjectivity in self-evaluations of health. Given that self-evaluation about the severity of illness is an observed variable, the social, cultural and psychological factors that shape their self-evaluations are different across patients. For the same level of severity of the same type of illness as judged by a doctor, different people can attach different importance.

Finally, unobserved heterogeneity in the choice set is also a problem to consider. Rural populations in general have limited information on available healthcare providers. In this case, it is possible that their choices are limited within some subsets of the whole choice set (for example, between village clinic and township health center, rather than among the whole set).

Between the end of 1980 and the middle of 2000, several factors may have led choice heterogeneity level to increase. The first factor is general income growth. The average GDP growth of China was 9% during 1989-2004, and GDP in 2004 was 8.07 times that of 1989 at current prices, and 3.8 times at constant prices. Incomes of rural and urban people in 2004 were respectively 4.88 and 6.86 times those of 1989 at current prices. Converted to incomes at constant prices, the income of rural people in 2004 was 2.3 times that of 1989. In our sample (see descriptive statistics in Table 5), the average per capita income and household assets in 2004-2006 are respectively 2.4 and 3.1 times those in 1989-1993.

An evident effect of general income growth would be that the choices became more heterogeneous among the patients because budget constraints became softer. People would tend to make their choices more on the functions of such factors as quality and reputation of the healthcare providers. They become less sensitive to the price of healthcare and the heterogeneity of price effects would reflect growing impact of the unobservable provider attributes and patient taste variations. General income growth could also reduce distance effect and make the impact of distance on preference more heterogeneous.

Another factor affecting choice heterogeneity is population aging. In 1990, the population more than 65 years old represented 5.57% of the total population. This ratio reached 9.07% in 2005, with 9.48% and 8.12% respectively for rural and urban populations (2005 Chinese population statistic yearbook; 2007 Chinese population and employment statistic yearbook). This means that the percent of the aged population has nearly doubled during this period. For the samples, as average age increased from 44 to 56 and with the share of aged people over 65 doubled, and their health conditions less favorable, patients would be less sensitive to price and their choices would be more affected by other factors. Besides unobservable healthcare provider attributes and patients' tastes, there are a lot of aging-specific factors. For example, when patients are aged, the relationship within the households, especially the relationship between the aged parents and younger members (sons, daughter-in-law) may lead to very different price sensitivity. Another evident effect is that as aged people like proximity, there is a stronger distance effect and reduced heterogeneity of distance impacts.

During this period, there was also significant supply side changes that allowed the choice set to be enlarged and more diversified. The number of village clinics was significantly reduced. One more alternative of choice reflecting the development of private healthcare providers was added in the second sample, while in the first 1989-1993 sample, private healthcare providers were absent. The enlargement of the extent of choice set potentially could increase heterogeneity since provider-specific attributes and patient-specific tastes attached to the new alternative are added up.

To summarize, with the increases in income and age and enlargement of the choice set, price effect on choice must be unambiguously more heterogeneous in the second period. Their impact on distance effect is uncertain, depending on which influence is more important: the income growth that reduces distance effect but increases its heterogeneity, or the population aging that increases distance effect and reduces its heterogeneity. The evolution of heterogeneity due to income growth and population aging discussed so far is based on theoretical and logical inferences. One advantage of MMNL used in this work is that it allows for testing the validity of these inferences through measuring preference heterogeneity.

3. Data and Econometric Modeling

3.1. Data

Data are from the CHNS database edited by the Carolina Population Center (CPC, University of North Carolina).[1] The survey covers about 16,000 individuals from more than 3,000 households (about two-thirds from rural and one-third from urban populations) in nine representative provinces. It is a longitudinal survey with seven waves (1989, 1991, 1993, 1997, 2000, 2004, and 2006).

We were interested in the starting and ending periods where a difference in the degree of preference heterogeneity is expected. So we decided not to keep data from the middle of the period and to build two samples: one for the first period and the other for the second. Within each sample, we ensured that income, healthcare prices and supply conditions were not significantly evolved over time. The number of the interviewed who were ill was smaller in the first waves than in the last (population aging is seemingly the main cause). So to keep some equilibrium between the two samples, we merged three time periods of two-year intervals (1989, 1991 and 1993) for the first sample and two time periods of two-year intervals (2004 and 2006) for the second sample, with 2,117 and 2,594 observations respectively. The last waves did not include individuals under 18 years old as the first waves did. We conducted a logistic regression analog of the Chow test to check whether the healthcare demand of the under-18 individuals differed from that of the over-18 ones (cf. Demaris, 2004). The results showed that the two models indeed differed. Consequently, observations of individuals under 18 were removed. Finally, our samples included 1,457 rural people who reported having been ill in 1989, 1991 or 1993, and 2,594 people who reported being ill in 2004 or 2006.

As our data panel included attrition and replacement, we checked the frequency of the patients and whether attrition was non-random. In the 1989-1993 sample, only 11.6% and 0.06% patients were surveyed two and three times; in the 2004-2006 sample, 16.3% patients were surveyed two times. CHNS data collectors have not given more details on attrition. Nevertheless, as Deaton (1997) stated, the rate of refusal of participation is lower in

[1] We thank the National Institute of Nutrition and Food Safety, China Center for Disease Control and Prevention; the Carolina Population Center, University of North Carolina at Chapel Hill; the National Institutes of Health (NIH; R01-HD30880, DK056350, and R01-HD38700); and the Fogarty International Center, NIH, for financial support for the CHNS data collection and analysis files since 1989. We thank those parties, the China-Japan Friendship Hospital, and the Ministry of Health for support for CHNS 2009 and future surveys.

developing countries. It must be still lower in rural China since political institutions exert strong control. Villagers in and out of participation must be mainly attributable to their absence, their moves or their deaths. Therefore, attrition can be regarded as random.

3.2. Model Specifications

Let the utility of a patient $i \in [1, I]$ be a function of health status, h, and non-health consumption, x.

$$\boldsymbol{U = U(h_i, x_i)} \tag{6}$$

Health status, h, is determined by the quantity and quality of healthcare (C) and other health inputs (e.g., sanitation), food consumption (F); and individual attributes like age, gender, education and income (R).

$$\boldsymbol{h_i = h(C_i, F_i, R_i)} \tag{7}$$

Healthcare demand is a function of the price of healthcare (p) and the distance to the healthcare provider (D). The importance of D is that distance not only implies cost of access, but also reflects the reputation and quality of providers.[2]

$$\boldsymbol{C_i = C(p, D)} \tag{8}$$

Finally, the other health input, F, is a function of expenditures on these inputs (E_i).

$$\boldsymbol{F_i = F(E_i)} \tag{9}$$

With equations (1) to (4), we have the indirect utility function in the case where individual i chooses healthcare provider j in which $y_i - p_j - E_i$ is the budget for non-health consumption (y is income).

$$\boldsymbol{V_j^* = U\big(h\big(C_j(p_j, D_j), F(E_i), R_i\big), y_i - p_j - E_i\big)} \tag{10}$$

Among the healthcare provider alternatives, the patient will choose the one that maximizes his/her indirect utility function. This is expressed by equation (6).

$$\boldsymbol{V_j = 1, \text{if } V_j^* = Max(V_1^*, V_2^*, \dots V_J^*)}$$

$$\boldsymbol{V_j = 0, \text{otherwise}} \tag{11}$$

To make the model amenable to econometric estimation, we must define a functional form of the above indirect utility function. This is expressed by equation (7) in which the first term on the right is the deterministic component of utility in the function of the above-defined four types of attributes and the second term is a disturbance term. The term E_i is unobserved and is treated as one part of the error term.

[2] Large healthcare providers must be set in towns or in cities. Consequently, their distance is farther than small healthcare providers in the proximity of the rural villages.

$$\boldsymbol{V_j = V_j^*(p_{ij}, D_{ij}, y_i, R_i) + \varepsilon_{ij}} \qquad \textbf{(12)}$$

Equation (7) must be parameterized to allow estimations. The first term can be rewritten as:

$$\boldsymbol{V_j^*(.) = Z_{ij}\beta_z + X_i\beta_{xj}} \qquad \textbf{(13)}$$

The X variables are patient-specific characteristics such as age, marital status, insurance status and income. The Z variables are alternative health provider-specific characteristics such as distance, price, healthcare quality and so on. In these defined variables, we have

$$\boldsymbol{V_j = \alpha_j + \beta_1 p_{ij} + \beta_2 D_{ij} + \beta_{3j} y_i + \beta_{4j} R_i + \varepsilon_{ij}} \qquad \textbf{(14)}$$

The variable p, the healthcare price, and D, the distance to healthcare provider are two provider-specific variables. The y, income and R, individual attributes other than income are patient-specific variables. Thus in our econometric estimations, p and D are kept constant across options while y and all components of R vary across options.

If equation (14) is estimated with MNL, the basic form of the MMNL, and with alternative specific constants α_j and attributes x_{ij} (here, x represents both z and x variables in the equation (13)), the result will be:

$$\boldsymbol{Prob(j)} = \frac{\exp(\alpha_j + \beta_j' x_{ij})}{\sum_{q=1}^{J} \exp(\alpha_q + \beta_q' x_{iq})} \qquad \textbf{(15)}$$

The difference between MMNL and MNL is that in the former, one part of the coefficients is random; in the latter, all coefficients are non-random. In equation (15), β_j' is composed of β_{ji} with

$$\boldsymbol{\beta_{ji}} = \begin{cases} \boldsymbol{\beta_j + \sigma_j \eta_{ji}\ if\ random} \\ \boldsymbol{\beta_j'\ if\ non-random} \end{cases} \qquad \textbf{(16)}$$

where $\beta_j$is the population mean, $\eta_{ji}$is the individual specific heterogeneity, with mean 0 and standard deviation 1, and σ_j is the standard deviation of the distribution of β_{ji} around β_j. The elements of β_{ji} are distributed randomly across individuals with fixed means.

We set both price and distance to healthcare providers as random variables. It would be interesting to estimate the heterogeneity in the preferences for both price and distance. They may have a substitutive feature: when people's is more sensitive to price, they may less care about the distance; that is, they may accept less expensive but more distant providers. In contrast, when they are less sensitive to price, they may prefer a less distant provider.

Given that η_{ji} are individual specific, σ_j will reflect unobserved random disturbances: the source of the heterogeneity. Thus in the population as stated above, if the random terms are normally distributed,

$$\boldsymbol{\beta_{ki} \sim Normal \left[\beta_k + \delta_k^{'} w_i, \sigma_k^2\right]} \quad \textbf{(17)}$$

Equation (17) has useful empirical implications and we will return to them in discussing their application. As the usual choice, we will use the normal distribution. Finally, to make our model more realistic, we will allow the two random parameters to be correlated.

3.3. Definitions of Variables

Table 1 presents all variables that were used and their definitions. The first five items (V, T, C, O, S) concern the dependent variable spread in a selected set of healthcare providers. All the following variables concern the independent variables. With the exception of the first five and the last three, all the remaining variables, are individual-specific attributes. The last three variables were used to take into account the environmental features. Rural population rate is a proxy of the development level of the village; village size is a proxy of the village clinic's size; and suburb reflects the proximity of the village to the urban medical infrastructure.

Table 1. Variable definitions.

Village-C (V)	=1 if the choice of treatment is village clinic; =0 otherwise.
Town-C (T)	=1 if the choice of treatment is township health center; =0 otherwise.
County-H (C)	=1 if the choice of treatment is county or higher level city hospital; =0 otherwise.
Other-type (O)	=1 if the source of treatment is pharmacy, private clinic and other clinic; =0 otherwise.
Self-care (S)	=1 if self-treatment is chosen; =0 otherwise.
P_j	Medical expense at constant prices of alternative j after eventual reimbursement by insurance multiplied by 10^{-3}; j=V, T, C, O, S. The expense of self-care is assumed =0.
$Dist0_j$	=1 if distance <0.5 km; =0 otherwise; j=V, T, C, O.
$Dist1_j$	=1 if distance >=0.5 km & <3; =0 otherwise; j=V, T, C, O.
$Dist2_j$	=1 if distance >=3 km &<10km; =0 otherwise; j=V, T, C, O.
$Dist3_j$	=1 if distance >=10 km; =0 otherwise; j=V, T, C, O.
Age	Age of the patient in the wave.
Female	=1 if the patient is female; =0 if male.
Marital	=1 if the patient is married; =0 otherwise.
Edu_level	=1 graduated from primary school; =2 lower middle school degree; =3 upper middle school degree; =4 technical or vocational degree; =5 university or college degree; =6 master's degree or higher.
Urban_job	=1 if the patient's job is not farmer; =0 otherwise.
Farmer	=1 if the patient's job is farmer; =0 otherwise.
No_job	=1 if the patient has not job;=0 otherwise.
No_insured	=1 if the patient is not insured; =0 otherwise.
Urban_insurance	=1 if for family members, the patient's insurance is one of the following types: commercial, free medical, workers compensation, and for the members that are urban employee, pass-way model, block model, catastrophic disease; =0 otherwise.
Cooperative_insurance	=1 if the patient's insurance type is rural cooperative; =0 otherwise.
Other_insurance	=1 if the patient's insurance is other than Urban_insurance and Cooperative_insurance (they include among others Health insurance for women and children, EPI (expanded program of immunization) and insurance for children); =0 other wise.
Severity	=1 if the illness or injury not severe; =2 somewhat severe; =3 quite severe.
Fever	=1 if individual suffered from fever; =0 otherwise.
Chronic	=1 if individual suffered from chronic diseases; =0 otherwise.
Other_deseases	=1 if individual suffered from diseases other than fever and chronic diseases; =0 otherwise.
Hhsize	The number of the household members.
Income	The annual per capita income at constant prices of the household multiplied by 10^{-3}.
Asset	The annual household value of the asset index.
Rural_popu_rate	The share of the rural employees in total labor of the village.
Village_size	The household number of the village multiplied by10^{-3}.
Suburb	=1 if the village is near a city; =0 otherwise.

The CHNS database provides household per head annual income at a constant price. The variable "Income" was used to estimate the effect of income on the choice of healthcare provider. Nevertheless, we consider that income only partially reflects the economic and financial states of households and individuals. Furthermore, linked with the specifics of farm activities, incomes are often too volatile and some households have declared negative income. Another problem is the extent to which incomes are measured with non-random errors. Thus, following several authors (Sahn and Stifel, 2000; Filmer and Kinnon, 2008), we judged it necessary to build an asset index and simultaneously used income and asset to measure the income and wealth effect. It could be assumed that their impact on healthcare choice can be sensibly different. For instance, income could have a stronger effect on the provider choices (including self-care) in the case of relatively moderate illness. Asset could be more influential on choices in the case of serious illness, since an important expenditure is concerned. Therefore, the simultaneous use of income and asset as explanatory variables could address the distinct effects. We used the following items for asset index:

1) Drinking water (4 choices);
2) Toilet facilities (8 choices);
3) Kind of lighting (5 choices);
4) Kind of fuel for cooking (8 choices);
5) Type of ownership of house (6 choices);
6) Ownership of electrical appliances and other goods (the number of appliances varied between 15 to 18 according to the periods of survey, and this information was absent only in 1989);
7) Means of transportation (5 types);
8) Type of farm machinery (5 types); and
9) Household commercial equipment (6 types).

For each wave, we used principal components analysis to derive weights (Filmer and Kinnon, 2008) on the basis of all rural households surveyed in the CHNS project. Then we only kept the obtained asset index for the households that declared having patients. Coefficients of correlation between income and asset were 0.29 for both periods (1989-1993 and 2004-2006) and were significant at 1%.

One interesting feature of Asset index is that as all items contained in Asset index have qualitative features, and thus reflect to a larger extent (like Income) per capita rather than overall household wealth. This enhances their comparability. Since the correlation is not so high, both variables could be simultaneously introduced in the model.

A second point is how to compensate for missing prices of healthcare. MMNL requires the prices of all the alternative providers, while in the survey only the prices of the providers that the patients visited were recorded. So the prices of alternative providers that patients did not visit needed to be imputed. Following Gertler *et al.* (1987), Gertler and van der Gaag (1990), and Borah (2006), we used the Stata ICE program created by Royston (2004) to impute the lacking price data. All reported prices were converted at constant prices using the weights given by the CHNS data provider. The chosen predictors of prices included

16 variables: Age, Female, Marital, Edu_level, Urban_job, Farmer, Income, Severity, Year, Province, Urban_insurance, Cooperative_insurance, Other_insurance, Fever, Chronic, and hospitalized (=1 if hospitalized; =0 otherwise). The regressions were separately operated according to the healthcare provider choices (V, T, C and O). The descriptive statistics of imputed plus actual prices by type of providers are presented in Table 2.

Table 2 calls for some comments. First, comparing the two samples, income, asset, education level, healthcare price, the share of patients with insurance, and village size were meaningfully increased. Two other increases linked with population aging were the No_job (composed notably by the retired), and Chronic. Second, in general, the share of the big and middle hospitals (township health centers and county hospitals) in chosen healthcare providers increased from 30% to 32% in the favor of county hospitals (from 9 to 18%) and to the detriment of township centers (from 21 to 14). The share of small clinics (village clinics in 1989-1993 and village clinics plus other_type in 2004-2006) decreased from 48% to 33%. Their reduction of 15% seems to benefit to the self-care that had a growth of 14%.[3]

[3] Other-type includes in general very small healthcare providers that practice Chinese medicine near a pharmacy, or the retired doctors that open a clinic with elementary equipment. They are far from being a growing alternative force to the three principal healthcare providers.

Table 2. Descriptive statistics.

	1989-1993 (n=1457)				2004-2006 (n=2594)			
Sample distribution by provider choice	Mean	SD	Min	Max	Mean	SD	Min	Max
Village-C	0.48	0.50	0	1	0.22	0.41	0	1
Town-C	0.21	0.41	0	1	0.14	0.35	0	1
County-H	0.09	0.29	0	1	0.18	0.39	0	1
Other-type					0.11	0.32	0	1
Self-care	0.21	0.41	0	1	0.35	0.48	0	1
P_V	0.074	0.078	0	0.477	0.096	0.079	0	0.598
P_T	0.159	0.162	0	0.859	0.207	0.169	0	1.166
P_C	0.466	0.617	0	3.506	0.651	0.597	0	3.808
P_O					0.204	0.318	0	3.972
Dist0_V	1	0	1	1	1	0	1	1
Dist0_T	0.40	0.49	0	1	0.48	0.50	0	1
Dist1_T	0.39	0.49	0	1	0.36	0.48	0	1
Dist2_T	0.21	0.40	0	1	0.15	0.36	0	1
Dist3_T	0	0	0	0	0	0	0	0
Dist0_C	0.13	0.34	0	1	0.23	0.41	0	1
Dist1_C	0.16	0.37	0	1	0.22	0.42	0	1
Dist2_C	0.22	0.41	0	1	0.25	0.43	0	1
Dist3_C	0.49	0.50	0	1	0.30	0.46	0	1
Dist0_O					0.63	0.48	0	1
Dist1_O					0.26	0.44	0	1
Dist2_O					0.09	0.29	0	1
Dist3_O					0.02	0.15	0	1
Age	44.47	15.41	18	92	55.88	15.12	18	97
Female	0.53	0.50	0	1	0.57	0.49	0	1
Marital	0.84	0.37	0	1	0.80	0.40	0	1
Edu_level	0.98	1.06	0	5	1.17	1.21	0	6
Urban_job	0.26	0.44	0	1	0.13	0.35	0	1
Farmer	0.60	0.49	0	1	0.35	0.48	0	1
No_job	0.14	0.35	0	1	0.51	0.50	0	1
No_insured	0.80	0.40	0	1	0.64	0.48	0	1
Urban_insurance	0.15	0.36	0	1	0.10	0.30	0	1
Cooperative_insurance	0.03	0.17	0	1	0.25	0.43	0	1
Other_insurance	0.02	0.13	0	1	0.01	0.10	0	1
Severity	1.71	0.70	1	3	1.70	0.67	1	3
Fever	0.35	0.48	0	1	0.26	0.44	0	1
Chronic	0.13	0.33	0	1	0.34	0.47	0	1
Other_diseases	0.52	0.50	0	1	0.40	0.49	0	1
Hhsize	4.40	1.50	1	13	3.66	1.69	0	13
Income	2.91	2.26	0.45	22.20	7.03	8.03	0.18	210.95
Asset	0.39	0.77	-1.05	3.08	1.20	0.96	-0.62	3.87
Rural_popu_rate	0.52	0.34	0	1	0.41	0.30	0	1
Village_size	0.66	0.74	0.03	6.00	1.01	1.19	0.04	8.00
Suburb	0.28	0.45	0	1	0.24	0.43	0	1

4. Results and Comparisons

In this section, we compare and analyze the results of MNL and MMNL estimations. Tables 3 and 4 respectively contain the regression results of the 1989-1993 and 2004-2006 data samples.

The software used for both models is Nlogit; MMNL estimates are obtained with 100 Halton draws. We first compare model fits. In both periods, MMNL yield higher likelihood values, indicating that the explanatory power of the mixed logit is greater than with standard logit. Another method is a likelihood ratio test generally used in comparison between MMNL and MNL. It is also significant at less than 0.01, meaning that MMNL provides improved fits over MNL. As indicated in the Nlogit user guide, *"the 'R-squareds' shown in the output are R^2s in name only. They do not measure the fit of the model to the data"*; so we just provide McFadden Pseudo R2 for MMNL. Chi squared tests are highly significant for both models. Two other measures commonly used to compare competing regression models are the Akaike information criterion (AIC) and Bayesian information criterion (BIC). These measures account for both the goodness of fit of the model and its parsimony. Each measure penalizes a larger model for using additional degrees of freedom while rewarding improvements in goodness of fit. The BIC places a higher penalty on using degrees of freedom than AIC. According to AIC, MMNL is better while according to BIC, MNL is preferred. Thus the results are not conclusive.

Assuming individual rationality, a negative price effect is expected since, if the good is a normal good following the law of demand states, as price increases, the demand for a good will decrease. From Table 3, in 1989-1993, according to both models, there were clear price effects. The estimated means are -0.377 and -1.606 respectively for MNL and MMNL, and the first is significant at 5% and the second at 1%. The coefficients of random variables in the MMNL are consistently of greater magnitude (in absolute terms) than those from the MNL. Revelt and Train (1998) had similar results that the mean coefficients of MMNL are higher than those of MNL. According to them, this is not surprising since a random parameter model decomposes the unobserved portion of utility and normalizes parameters on the basis of part of the unobserved portions.

Table 3. Regression results on1989-1993 sample.

	MNL			MMNL		
	Village-C	Town-C	County-H	Village-C	Town-C	County-H
PRICE	-0.377 (0.169)**			-1.606 (0.414)***		
Distance1	0.049 (0.155)			-0.135 (0.311)		
Distance2	-0.346 (0.197)*			-0.494 (0.287)*		
Distance3	-0.407 (0.312)			-4.323 (1.749)**		
intercept	0.102	-1.467	-2.86	0.091	-1.520	-3.349
	(0.596)	(0.727)**	(0.943)***	(0.605)	(0.780)*	(1.257)***
Age	-0.018	-0.016	-0.04	-0.018	-0.016	-0.005
	(0.006)***	(0.007)**	(0.009)	(0.006)***	(0.007)**	(0.011)
Edu_level	0.109	0.070	0.027	0.114	0.072	-0.033
	(0.087)	(0.103)	(0.130)	(0.088)	(0.110)	(0.172)
Women	0.432	0.300	0.268	0.440	0.270	0.401
	(0.152)***	(0.181)*	(0.235)	(0.153)***	(0.193)	(0.323)
Hhsize	-0.018	0.051	0.049	-0.018	0.047	0.111
	(0.048)	(0.058)	(0.074)	(0.049)	(0.062)	(0.095)
Asset	0.382	0.424	0.110	0.440	0.424	-0.195
	(0.149)**	(0.173)**	(0.220)	(0.153)***	(0.184)**	(0.301)
Income	-0.027	-0.023	0.059	-0.026	-0.023	0.130
	(0.037)	(0.042)	(0.049)	(0.037)	(0.045)	(0.072)*
Severity	0.443	0.786	0.938	0.484	0.910	0.977
	(0.111)***	(0.129)***	(0.167)***	(0.113)***	(0.148)***	(0.220)***
Marital	0.356	0.367	0.576	0.355	0.383	0.636
	(0.189)*	(0.231)	(0.310)*	(0.190)*	(0.248)	(0.399)
Urban_Insurance	-0.082	0.222	0.107	-0.067	0.276	0.221
	(0.288)	(0.342)	(0.394)	(0.293)	(0.364)	(0.489)
Cooperative_insurance	0.393	0.294	0.947	0.428	0.307	1.623
	(0.532)	(0.590)	(0.702)	(0.537)	(0.629)	(0.926)*
Urban_job	0.459*	0.243	0.240	0.462	0.196	0.244
	(0.276)	(0.331)	(0.383)	(0.280)*	(0.354)	(0.479)
Farmer	0.129	-0.035	-0.149	0.120	-0.064	-0.273
	(0.244)	(0.286)	(0.362)	(0.248)	(0.310)	(0.510)
Fever	-0.184	-0.518	-0.624	-0.218	-0.654	-0.721
	(0.153)	(0.186)***	(0.250)**	(0.155)	(0.204)***	(0.336)**
Chronic	0.043	-0.229	-0.103	0.071	-0.308	0.280
	(0.231)	(0.276)	(0.337)	(0.233)	(0.296)	(0.423)
Rural_popu_rate	0.403	0.382	-0.068	0.398	0.315	0.088
	(0.341)	(0.401)	(0.533)	(0.344)	(0.429)	(0.749)
Village_size	0.227*	-0.107	0.390	0.237	-0.123	0.520
	(0.134)*	(0.193)	(0.158)**	(0.138)*	(0.206)	(0.181)***
Suburb	-0.088	-0.710	-0.240	-0.070	-0.718	-0.091
	(0.272)	(0.337)**	(0.423)	(0.276)	(0.369)*	(0.571)
Province dummies	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)
Wave dummies	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)
SD of parameter distributions						
PRICE				2.100 (0.433)***		
Distance1				1.083 (0.700)		
Distance2				0.795 (0.545)		
Distance3				3.935 (1.070)***		
N	1457			1457		
Log-like	-1663.084			-1648.234		
McFadden Pseudo R2				0.184		
Chi Squared	248.499			743.195		
Significance level	0.00000			0.00000		
AIC	3496.169			3486.467		
BIC	3945.320			3988.460		

Note: Standard error is in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%.

Table 4. Regression results on 2004-2006 sample.

	MNL				MMNL			
	Village-C	Town-C	County-H	Other-Type	Village-C	Town-C	County-H	Other-Type
PRICE	0.010 (0.088)				-0.409 (0.191)**			
Distance1	-0.486 (0.095)***				-0.831 (0.205)***			
Distance2	-0.508 (0.124)***				-0.698 (0.193)***			
Distance3	-0.872 (0.170)***				-1.148 (0.235)***			
intercept	-1.070	-1.351	-1.239	-1.114	-1.073	-1.449	-1.283	-1.260
	(0.510)**	(0.576)**	(0.551)**	(0.639)*	(0.514)**	(0.619)**	(0.626)**	(0.680)*
Age	-0.0005	-0.006	-0.015	-0.010	-0.001	-0.006	-0.016	-0.010
	(0.005)	(0.006)	(0.005)***	(0.006)*	(0.005)	(0.006)	(0.006)***	(0.006)*
Edu_level	-0.057	-0.116	-0.101	-0.075	-0.057	-0.119	-0.106	-0.066
	(0.066)	(0.073)	(0.064)	(0.075)	(0.067)	(0.078)	(0.072)	(0.078)
Women	0.083	-0.051	-0.038	-0.098	0.083	-0.059	-0.050	-0.091
	(0.127)	(0.142)	(0.133)	(0.150)	(0.128)	(0.151)	(0.150)	(0.157)
Hhsize	-0.007	0.009	-0.015	-0.113	-0.007	0.010	-0.014	-0.125
	(0.039)	(0.044)	(0.041)	(0.049)**	(0.039)	(0.046)	(0.046)	(0.051)**
Asset	-0.143	0.089	0.202	0.059	-0.142	0.085	0.241	0.086
	(0.092)	(0.103)	(0.092)**	(0.110)	(0.092)	(0.110)	(0.104)**	(0.116)
Income	-0.004	-0.005	-0.003	-0.011	-0.002	-0.008	-0.002	-0.012
	(0.009)	(0.011)	(0.009)	(0.012)	(0.008)	(0.012)	(0.010)	(0.013)
Severity	0.388	0.930	1.124	0.621	0.406	1.042	1.252	0.678
	(0.095)***	(0.103)***	(0.098)***	(0.112)***	(0.097)***	(0.115)***	(0.118)***	(0.119)***
Marital	0.068	0.135	0.281	0.154	0.076	0.148	0.376	0.177
	(0.151)	(0.174)	(0.164)*	(0.182)	(0.153)	(0.186)	(0.184)**	(0.190)
Urban_Insurance	-0.354	0.158	0.456	0.136	-0.347	0.146	0.487	0.179
	(0.294)	(0.281)	(0.211)**	(0.278)	(0.296)	(0.302)	(0.240)**	(0.291)
Cooperative_insurance	0.257	-0.046	-0.199	0.131	0.247	-0.049	-0.236	0.118
	(0.163)	(0.190)	(0.191)	(0.211)	(0.165)	(0.203)	(0.215)	(0.222)
Urban_job	-0.039	0.045	-0.647	-0.288	-0.055	0.081	-0.722	-0.343
	(0.211)	(0.226)	(0.211)***	(0.241)	(0.213)	(0.242)	(0.237)***	(0.253)
Farmer	0.082	-0.073	-0.387	-0.070	0.083	-0.051	-0.452	-0.067
	(0.145)	(0.163)	(0.171)**	(0.182)	(0.146)	(0.175)	(0.191)**	(0.191)
Fever	0.914	0.383	-0.638	0.664	0.906	0.384	-0.746	0.702
	(0.144)***	(0.168)**	(0.183)***	(0.170)***	(0.146)****	(0.180)**	(0.203)***	(0.179)***
Chronic	-0.083	-0.138	-0.182	-0.414	-0.075	-0.133	-0.189	-0.424
	(0.143)	(0.154)	(0.137)	(0.176)**	(0.144)	(0.165)	(0.154)	(-0.184)**
Rural_popu_rate	0.612	-0.165	-0.036	-0.239	0.614	-0.244	0.009	-0.325
	(0.288)**	(0.329)	(0.346)	(0.376)	(0.291)**	(0.352)	(0.386)	(0.396)
Village_size	-0.104	0.026	0.083	-0.087	-0.103	0.031	0.096	-0.092
	(0.084)	(0.081)	(0.055)	(0.077)	(0.085)	(0.085)	(0.062)	(0.081)
Suburb	-0.420	-1.621	-0.133	-0.116	-0.399	-1.653	-0.191	-0.141
	(0.224)*	(0.263)***	(0.223)	(0.248)	(0.227)*	(0.277)***	(0.255)	(0.262)
Province dummies	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)
Wave dummies	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)	Yes (omitted)
SD of parameter distributions								
PRICE					1.375 (0.261)***			
Distance1					1.292 (0.338)***			
Distance2					1.131 (0.373)***			
Distance3					0.853 (0.357)**			
N	2594				2594			
Log-like	-3493.772				-3480.662			
McFadden Pseudo R2					0.166			
Chi Squared	954.192				1388.440			
Significance level	0.00000				0.00000			
AIC	7211.545				7205.324			
BIC	3945.320				3988.460			

Note: Standard error is in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%.

The most striking result is that in the 2004-2006 period, unlike in MMNL, price effect disappeared in MNL. As shown in Table 4, the coefficient of Price is 0.01 and is no longer significant. Nevertheless in the MMNL model, even though weaker than in 1989-1993, price effect was present with a coefficient of -0.409 and significant at 5%. Principally on the basis of this difference, we judge that the MNL analysis does not produce logical or consistent signs for price estimates. MMNL estimation of price effect is in line with our deduction: in 2004-2006, due to general income growth and population aging, patients' choices would reveal larger observed and unobserved heterogeneity, and price effect would decrease and became more heterogeneous. In the following analysis in Table 7, we finds that heterogeneity in price effects does increase in 2004-2006. The failure of the MNL model to predict weaker but existing price effect seems to be attributed to its inability to deal with heterogeneity, thereby leading to a biased estimate.

To reinforce this analysis, we also calculate marginal effects in terms of price elasticity. This method will provide more detailed information at the healthcare provider level while in Tables 3 and 4, the mean coefficients of price are only general indicators for all healthcare providers. In Table 5, price elasticity is calculated under MMNL and MNL using exactly the same variables as in Table 3 and Table 4. We observe that the trends of price elasticity are coherent with those of mean price coefficients obtained in regressions. In 1989-1993, the absolute value of price elasticity on average is higher with MMNL than with MNL. At the healthcare provider level, the only exception exists in County hospital. In 2004-2006, however, while price elasticity is absent with MNL, it appears with MMNL (except in the case of County hospital). Comparing 1989-1993 and 2004-2006 with MMNL results reveals that price elasticity in the first period is indeed higher than in the second period at the healthcare provider level. MMNL is superior to MNL in that in the former, price effect was weaker but always existent, while MNL fails to estimate this effect for the second period.

Table 5. Price elasticity of choice by provider type in two samples.

	1989-1993			2004-2006			
	Village-C	Town-C	County-H	Village-C	Town-C	County-H	Other-Type
MMNL	-0.0593	-0.1611	-0.0390	-0.0217	-0.0833	0.0366	-0.0391
MNL	-0.0149	-0.047	-0.162	0.001	0.002	0.005	0.002

Another way to compare the relevance of MMNL and MNL is to use their estimated price coefficients to compute the willingness-to-pay for illness severity. It is computed as the coefficient of severity divided by the coefficient of price in absolute value. As severity is classified into three degrees, willingness-to-pay for severity can be interpreted as the amount the patients are willing to pay for one (more) degree of severity. It seems that the results with MMNL appear more coherent. In general, the increases are higher (from 3.3 times for Village Clinic to 5 times for County Hospital) than income growth (2.3 times). Given the aging of the patients, this willingness-to-pay increase for severity seems reasonable. Willingness-to-pay in MNL for 2004-2006 is not presented due to the absence of significant price effect.

Table 6. Willingness-to-pay for severity by alternative (in Yuan).

	1989-1993		2004-2006	
	MNL	MMNL	MNL	MMNL
Village-C	1175	301		993
Town-C	2085	567		2548
County-H	2488	608		3061
Other-Type				1658

The second random variable is distance to healthcare provider. In accordance with the analysis on price effect, the coefficients of distances with MMNL are higher than with MNL. But unlike price effect in sign and significance, there are not meaningful divergences of distance effects between the two models (except Distance1 and Distance3 in 1989-1993). We distinguished four levels of distance: from Distance0 to Distance3 (see Table 1), and expect that other things being equal, patients prefer closer to farther healthcare providers. In 1989-1993, Distance1 is insignificant in both MMNL and one MNL. In 2004-2006, nevertheless, all Distance dummies are significantly negative, indicating that distant healthcare providers are less likely to be chosen. Further, from DISTANCE1 to DISTANCE3, the coefficients in absolute terms generally are rising, meaning that as distance is increased, the probability to be chosen declines. In comparing the results of 1989-1993 and 2004-2006, we observe that the impact of distance is stronger in 2004-2006 with larger coefficients in absolute values. This is a logical consequence of general population aging. Other things being equal, aged people have stronger proximity preference than younger people. [4]

One interesting question is while MNL fails in estimating price effect, why does it succeed in estimating distance effect in the second period? This seems to be a logical consequence of the difference in the degree of heterogeneity. As previously explained, the

[4] Distance3 is exceptional as its coefficient in 1989-1993 is higher than in 2004-2006 in absolute values. We argue that as Distance3 in 1989-1993 only covers county hospitals and the choice of county hospital represented only 9% of the total choices, its unusually high impact may reflect that in this period with low average income, the access to county hospitals was to a large extent a luxury health consumption, and consequently, unlike Distance3 in 2004-2006, it reflects to a large extent income effect instead of distance effect.

heterogeneity of the price effects on preference increases with general income growth and population aging, while their influences on the heterogeneity of the distance effects is uncertain. This depends on which influence is more important: the income growth that reduces distance effect but increases its heterogeneity, or the population aging that increases distance effect but reduces its heterogeneity. MNL fails to estimate price effect because the heterogeneity of the price effects on preference has increased. Nevertheless, as shown in the analysis in Table 7, heterogeneity in distance effects was either unchanged or reduced in 2004-2006. Therefore, MNL succeeds in estimating distance effect because the impact of distance on preference did not become more heterogeneous over the period. Consequently, the two seemingly different results affirm the same conclusion: MNL fails to provide good estimation when heterogeneity becomes important.

Another comparison is the quantity of information contained in the two models. MMNL makes available more information than MNL in that it estimates the extent to which patients differ in their preferences for providers. Unobserved heterogeneity is represented by the standard deviation parameters. In a MNL model, the opportunity to establish the role of the mean and variance influence of a particular variable would be denied. This is recognition of the amount of information loss that is caused by rigid model specifications.

The standard deviations of price parameters are 2.1 and 1.375 respectively for the two samples and both are significant at 1%, indicating that parameters do indeed vary in the population. Following equation (17), we can easily calculate the level of this heterogeneity with the criterion of the percentage of patients for which the coefficients of price are above zero. Table 7 provides evidence of the price heterogeneity imputed to unobserved sources. In 1989-1993, while about 80 % of patients followed the rule that demand falls as price rises, 20% of patients did not. In 2004-2006, the latter was doubled and rose to 38.30%, indicating that, in accordance with our reasoning, heterogeneity in price preferences has meaningfully increased in the second period with income growth and population aging. Heterogeneity in Distance1 is reduced and Distance2 is unchanged. Distance3 is reduced from 13.59% to 8.92%. In line with our reasoning that general income growth would positively, while population aging would negatively, affect the extent of heterogeneity of distance effects, then the final result depends on which force is stronger. The comparison of the coefficients of three distance dummies leads to concluding that the impact of aging exceeds that of income growth.

Table 7. Extent of heterogeneity measured by percentage of patients of which the coefficients of price or distance >0 (modified).

	1989-1993	2004-2006
Price	22.22%	38.30%
Distance 1	45.03%	26.00%
Distance 2	26.73%	26.86%
Distance 3	13.59%	8.92%

Note: Calculated with equation (12) and using the mean coefficients and SD of parameter distributions from Table 6.

Given that the other variables are patient-specific and do not vary with healthcare provider, they cannot be assigned to have a random term; their coefficients with MMNL and MNL are similar in sign and extent. As their interpretations are out of the scope of comparison between MMNL and MNL, we just provide a brief discussion.

The parameters of Income and Asset measure the extent to which richer patients have more access to healthcare than poorer patients. If they are significantly positive, the poorer patients are more likely to be excluded from healthcare services. According to regressions, while income effects were absent in both periods, asset effects were present for some choices. It seems to mean that the demand for healthcare was more a function of wealth than income. From Table 3 in 1989-1993, the coefficients of asset for Village clinic and Township health center are significantly positive, while in 2004-2006 (except for County hospital), asset is insignificant for all choices. In other words, in the first period the patients with more assets tended to choose village clinics and township health centers, while patients with low asset level choose more self-care. Given that in 1989-1993, the choices of village clinic and township health center represent 74% of the total choices, we conclude that while there was a wealth effect in 1989-1993, this effect is absent in the choices of village clinic and township health center and is transferred to more expensive healthcare providers: county hospital in 2004-2006. This evolution seems to be the consequence of the general income growth. It allowed fewer less fortuned patients to be excluded from grass-roots level healthcare providers, whereas this discrimination was still present for access to more expensive large healthcare providers.

As the share of patients having cooperative insurance had increased from 0.03% to 25%, we expected an insurance effect on the choice of healthcare provider. However, this effect is absent in both periods. One possible explanation is that the rates of reimbursement were in general too low.

Unlike in 1989-1993, in the less developed villages (with the share of rural labor as a proxy), the patients chose more village clinics in 2004-2006. This may be a village-level income inequality effect: in less developed villages, patients had less access to healthcare providers outside the village.

Another interesting result is that when illness type is fever, in 1989-1993, the patients prefer self-care. However in 2004-2006, the patients preferred going to see one of the provider types (except county hospital). It seems that as the aged patients have significantly increased in 2004-2006, fever is a more severe symptom for aged people than for younger people.

Significant positive coefficients are associated with the severity of illness for all provider types over self-care. This indicates that sicker patients prefer going to see doctors. It is interesting to observe that the coefficient of Village clinic just slightly falls and those of Township health center and County hospital increased during the period, meaning that in the case of serious diseases, the probability to go to village clinics decreased, while the probability to go to township health centers and county hospitals increased. Other-type is an intermediate solution between them.

5. Conclusions

MNL models have been shown by many researchers to produce inconsistent parameter estimation in the presence of unobserved heterogeneity due to the inherent IIA property. MMNL provides a flexible framework for incorporating both observed and unobserved factors that influence the provider choice decision. An empirical issue would be to verify in the presence of preference heterogeneity, and whether MMNL gives superior performance over MNL.

We constructed two samples surveyed within the same regions but with an interval of 18 years. We focused on two factors that could lead patients' choice heterogeneity to vary: general income growth and population aging. With the presence of a larger degree of heterogeneity in the 2004-2006 sample compared to the 1989-1993 sample, we applied both MNL and MMNL models with exactly the same variables. We expected that in the second period, the performance of MNL would be lower than in the first period while that of MMNL remains stable.

We found that in both periods, MMNL yields higher likelihood values and a likelihood ratio test indicated that MMNL provides improved fits over MNL. In 1989-1993, according to both models, there were clear price effects. However in 2004-2006, unlike in MMNL, price effect disappeared in MNL. Principally on the basis of this difference, we judged that the MNL does not produce logical or consistent signs for the estimates of Price. Our estimations have proven that the heterogeneity in price preferences was higher in the second than in the first period. We concluded that the failure of the MNL model to predict weaker but existing price effect seems to be attributed to its inability to deal with heterogeneity, thereby leading to a biased estimate.

The second random variable was distance to healthcare provider. Unlike in price effect, there were not meaningful divergences of distance effects between the two models in sign and significance. This was also a logical outcome. MNL failed to estimate price effect because the heterogeneity of the impacts of price on preference had increased. It succeeded in estimating distance effect because, as the estimation results suggested, the impact of distance on preference did not become more heterogeneous over the period. Therefore, the two seemingly different results affirmed the same conclusion: MNL failed to provide good estimation when heterogeneity became important.

The coefficients of Price and Distance with MMNL being higher than with MNL indicated stronger price and distance effects in MMNL estimations. Another advantage of MMNL relating to MNL is the possibility to measure the extent of heterogeneity of the effects from random variables. MMNL estimates confirmed our logical deduction that preference heterogeneity varied with income growth and population aging.

We conclude that in healthcare demand choice, in the presence of important heterogeneity, researchers are cautioned when interpreting the estimation results produced with the MNL model.

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