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What does demand heterogeneity tell us about health care provider choice in rural China?

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Abstract

The objective of this paper is twofold: 1) to fill the gap in the health care literature with the estimation of the price and distance effects on health care provider choices by households in the presence of varying demand heterogeneity, 2) to contribute to estimation robustness by confronting the performance of the mixed multinomial logit (MMNL) and the multinomial logit (MNL). We built a database of two samples of patients surveyed within the same regions in rural China over a time interval of 18 years, and presumed varying demand heterogeneity due to income increase and people aging.

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Keywords: price effect, distance effect, health care choice, preference heterogeneity, multinomial and mixed logit model, estimation robustness, Chinese rural households.

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…/… We find that while the mean price and distance negative effects on patients choice were present in both time periods, their differences in heterogeneity, which were confirmed with the MMNL, could have crucial importance in avoiding erroneous policy making based merely on mean price and distance effects. We also find that while both the MNL and the MMNL are able to predict price and distance effects with low heterogeneity, only the MMNL appears able to detect the price effect when heterogeneity is high. This finding has policy implications and suggests using caution when interpreting estimation results with the MNL in cases of high heterogeneity.

1. Introduction

The demand for health care and the effects of price and distance on patients' provider choices have been subject to extensive studies that carry important policy implications. For instance, a weak price effect implies a high demand for more expensive and high quality health care services, and thus suggests the need for resource allocation towards large and well-equipped hospitals. Studies on distance effect can help to optimize geographical allocation of medical resources. For example, a strong distance effect suggests the need for a more decentralized system with small and nearby health care providers.

There is, however, a serious gap on how these effects manifest and are interpreted in the presence of demand heterogeneity among patients. By demand (or choice) heterogeneity, we mean the extent of the difference in demand among the patients in function of the health care prices and of the distances of the health care providers. In other words, they are the variances of the price and distance effects across the patients. This issue is crucial for health care because first, some significant changes in heterogeneity could change the sense or the extent of the mean price and (or) distance effects. Second, two cases with the same mean price and (or) distance effects, but different in heterogeneity should be treated differently because, as shown in the subsequent sections, this difference gives rise to different policy implications. As an illustration, a recent study (Audibert et al., 2016) has questioned the need to merge some township hospitals in China. To justify this need, it will not be sufficient to estimate the mean price and distance effects on provider choices only. The heterogeneity of these choices is also crucial. Another example is that this heterogeneity may have implications for setting up reimbursement rates in China's New Cooperative Medical System, which has expanded rapidly since 2003 (Barber and Yao, 2011).

The first objective of this study, therefore, is to fill the gap in the health care literature with the estimation of the effects of price and distance on health care provider choice in the presence of various types of demand heterogeneity and illustrate the importance of taking this heterogeneity into account in policy making.

The idea on how to take the samples is to focus on a similar population group and observe their health care choices over two periods during which their demand heterogeneity has meaningfully changed. This requires the collection of data in a similar region over a fairly long period where significant economic changes have occurred to cause divergent demand heterogeneity. We construct two samples of patients from the same villages of nine Chinese provinces over two periods: 1989-1993 and 2004-2006. We focus on the two most important factors that could lead patients' provider choices to become more (or less) heterogeneous: During two periods, the average real income per capita were more than doubled, along with a sharp increase in income inequality, and the average age of patients significantly increased. It is reasonable to assume that an increase in patient income, while causing a weaker price effect, will lead provider choices based on health care price to be more heterogeneous, because these choices are henceforth made on the basis of their difference in preferences on quality, and other observed and unobserved aspects of health care. We can also expect that more elderly patients in poorer health would be less likely to choose a provider based on health care price and more likely to choose providers based on proximity. Therefore, choice heterogeneity based on price and distance could be expected to be lower with population aging.

Our second objective is methodological. There have been a number of studies with divergent conclusions on the estimation robustness of two econometric models. The conditional multinomial logit model (MNL) is most often used for estimating health care demand, but is considered by some people as not suitable in cases of high choice heterogeneity. The mixed multinomial logit model (MMNL), which has emerged more recently, offers the possibility of decomposing individual preference. Comparing the performance between the two models in the presence of preference heterogeneity will allow us to contribute to the existing literature on the relative robustness of these two models.

The first finding of our study is that while the mean price and distance effects on provider choices by patients were present in both time periods, their presumed differences in heterogeneity are confirmed with MMNL testing. More precisely, during the second period, while the heterogeneity of choices based on price increased, mainly due to aging of patients, the heterogeneity of choices based on distance decreased. This information on heterogeneity, which is not available with conventional studies that use the MNL method, will be shown to have crucial importance in preventing erroneous policy making merely on the basis of the mean effects of price and distance. It will also contribute to better meeting health care demands, fine-tuning the piloting of the health care system, and rationalizing the geographic distribution of healthcare facilities in China.

The second finding is that, while both the MNL and the MMNL are able to predict price and distance effects with low heterogeneity, only the MMNL detected the price effect when heterogeneity was high. This finding suggests using caution when interpreting estimation results with the MNL in cases of high heterogeneity.

The remainder of the paper is organized as follows. Section 2 introduces the literature on the estimations of price and distance effects and explains why this study focusing on demand heterogeneity in rural China fills a gap in the literature. It also presents the issue on the choice between the MNL and MMNL models and the contribution with this study. Section 3 sets up the econometric model and describes the two-period samples. Section 4 analyzes the results and Section 5 concludes.

2. Issues on heterogeneity in health care demand

2.1. Previous work on price and distance effects

There is abundant literature on health care provider choice in developing countries. As explanatory factors, income and price have always received special attention. Results obtained have led to contradictory conclusions. Several studies have found that income and price had significant elasticity on provider choice (Lavy & Guigley, 1991; Sahn, Younger & Genicot, 2003; Ntembe, 2009; Lopez-Cevallos & Chi, 2010), while others have found that these factors were not important determinants (Akin, Griffin, Guilkey & Popkin, 1986; Mocan, Tekin & Zax, 2004; Lindelow, 2005) whereas the perceived quality of health care had a greater effect (Mariko, 2003; Cissé, 2004). The debate is old and still continues with the recent policy positions in favor of removing user fees to foster universal coverage approaches.

As the debate is not closed and the literature findings have not been clear, several authors have undertaken systematic literature reviews on access to care (Lagarde & Palmer, 2008 & 2011; McPake, Brikci, Cometto, Schmidt & Araujo, 2011; Ridde & de Sardan, 2013; Dzakpasu, Powell-Jackson & Campbell, 2014). Three points have emerged. First, despite abundant literature, the diversity of the objectives and methods used make it difficult to draw definitive conclusions. Second, upon the basis of the included rigorous relevant studies, price of health care is a determinant of the utilization of health care services; however, its effect does not appear to be independent of the quality of care and may vary across countries and over time. Third, the weakness of the methodology has hampered the strength and reliability of literature findings on income and price effects. Thus, there is a need for additional research with appropriate methodologies that can help debates and aid policy makers.

One of the missing points in previous works is the absence of theoretical and empirical considerations on demand heterogeneity. While income and price effects reflect the mean trend of patients' provider choices, the question on the heterogeneity of these choices is also in need to be addressed. With the same mean trend but a different degree of heterogeneity, implications for government policy could be quite different. It is also possible that increasing demand heterogeneity could change the mean effect. Therefore, the study on heterogeneity in relation to mean effects could significantly contribute to our understanding of health care demand.

This analysis on income and price effects also applies to studies on the distance effect on provider choice. This effect is important in developing countries where access to transport is more costly than in developed countries. The distance effect, especially its heterogeneity, has rarely been examined except by Borah (2006) in the case of India.

2.2. Why rural China provides a good case for demand heterogeneity

Since the early 2000s, China has adopted a set of measures that have gradually led to a profound reform of the health care system. These measures have aimed to regulate the health care supply, change the modes of health care financing and improve health care accessibility from the demand side. They combine command and control approaches with an alignment of incentives in order to improve people's health and welfare and also to influence the behavior of patients and providers to meet public policy objectives.

Between late 1980 and mid-2000, China achieved some profound social economical changes. The first was general income growth. The average GDP growth of China was 9% between 1989 and 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 households in 2004 were 4.88 and 6.86 times those of 1989, respectively, at current prices. Converted to incomes at constant prices, the income of rural households in 2004 was 2.3 times that of 1989. In our sample, the average per capita income and household assets in 2004-2006 are 2.4 and 3.1 times those in 1989-1993, respectively.

An obvious effect of general income growth would be that health care choices became more heterogeneous among patients because budget constraints decreased.[1] People would tend to base their provider choices more on factors such as the quality and reputation of health care providers. They would become less sensitive to the price of health care, and the heterogeneity of price effects on provider choices would reflect a growing impact of unobservable provider attributes and patient preference variations. General income growth could also reduce distance effect and make the impact of distance on preference more heterogeneous because the choices become less constraint by the transports costs.

Another factor that affects choice heterogeneity is population aging. In 1990, 5.57% of the total population were over 65 years old. By 2005, this percentage had nearly doubled to 9.07%, with 9.48% and 8.12% for rural and urban populations, respectively.[2] In our samples, with average age increased from 44 to 56 and the percentage of people over 65 doubled and their health naturally decreased, patients' provider choices would be, in general, less sensitive to price and more affected by some other factors. Besides some health care provider attributes and individual patient preferences, there are many aging-specific factors. For example, relationships within households, especially between elderly parents and adult children (sons, daughters-in-law) may lead to very different levels of healthcare sensitivity. As elderly people tend not to like to travel, there is a stronger distance effect and reduced heterogeneity of distance impacts.

Along with income growth and aging, several sources of unobservable heterogeneity can

[1] More precisely, income growth results higher heterogeneity in choice if this growth is higher than the growth of heath care costs. From the following Table 2 on descriptive statistics, we know that this condition is fully satisfied in our samples.

[2] They are calculated on the basis of the 2005 Chinese population statistic yearbook and the 2007 Chinese population and employment statistic yearbook.

potentially evolve and affect changes in demand heterogeneity: on the side of unobserved health care provider attributes, there are at least two: 1) factors in non-price competition and 2) transport accessibility. For same type of health care provider (such as a county hospital), equipment levels, quality and experience of staff vary. In particular, the perception of 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 health care provider is an unobserved factor. A farther distance is counterbalanced by, for instance, more frequent public transport.

On the side of personal preference variations of rural patients, there can be several sources. First, there are differences in judgments on the efficiency of Chinese medicine across patients. We can expect that, patients who believe more in Chinese medicine tend more to choose smaller health care providers, while those who distrust Chinese medicine tend toward larger health care providers. Second, there are differences in patient perceptions about the effectiveness of the same type of health providers due to their past experiences in health care. Third, there are differences in the connections with personal relationship networks. Given that this network is so crucial in China, the extent of this network with the same type of health care provider varies across patients. All else being equal, one patient may prefer a township health center over a county hospital simply because he has a relative working there. Fourth, there is subjectivity in self-assessment of health. Given that self-assessment of the severity of illness is an observed variable, the social, cultural and psychological factors that shape self- assessment clearly vary from patient to patient.

Unobserved heterogeneity in the choice set is also a problem to consider. Rural populations in general have limited information on available health care providers. As a consequence, it is possible that their provider choices are limited within some subsets of the whole choice set (for example, between village clinic and township health center, rather than among all available health care facilities).

Along with income growth, there were also significant supply side changes that enlarged and diversified the choice set. Whereas the number of village clinics was significantly reduced (-30%) during the two periods, an additional choice alternative : private health care providers was added and represented over 10% of patients' choices in the second sample, while in the first 1989-1993 sample, private health care providers were absent. The enlargement of the extent of the choice set could potentially increase heterogeneity.

To summarize, with the increases in income and age of our patient samples and enlargement of the choice set, all above-mentioned sources of heterogeneity are subject to significant change, and thus enlarge the extent of heterogeneity in patients' health care preferences. The impact of price effect can be expected to be more heterogeneous in the second period, but distance effect is expected to be uncertain, depending on which influence is more important: the income growth that reduces the distance effect but increases its heterogeneity, or the aging of the population that increases the 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. They constitute the assumptions for our subsequent empirical tests.

2.3. MNL and MMNL in the presence of heterogeneity

McFadden's choice model (McFadden, 1974), which relies on the conditional multinomial logit (MNL) model, has long been the leading tool for empirical studies. As the MNL model is based on the Independent and Identically Distributed (IID) assumption, and hence on the Independence of Irrelevant Alternatives (IIA) assumption, its failure to deal with heterogeneity is deemed capable of resulting in inferior model specification, spurious test results and invalid conclusions (Louviere *et al.* 2000; Train 2003). The mixed multinomial logit (MMNL) is similar to the MNL except that it allows parameter estimates to vary across individuals. According to the authors of the MMNL, in the presence of large-scale heterogeneity, the MMNL that relaxes IID will lead to marked improvement in estimations relating to the MNL. The MMNL leads to gaining generality, but the estimation simplicity that characterizes the MNL is lost. Thus, when the MNL is not biased, it is preferred. Furthermore, the MMNL is believed to provide a flexible framework for incorporating both observed and unobserved factors that influence the provider choice decision. The MMNL allows the parameter associated with each observed variable to vary randomly across individuals, and the variance among these parameters reflects 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 (Train 2009).

To illustrate the difference between the MNL and the MMNL, consider the following utility function:

$$U_{ij} = \alpha_i Z_{ij} + \varepsilon_{ij} = (a + \xi_i)Z_{ij} + \varepsilon_{ij} \qquad (1)$$

where U_{ij} is the utility of individual i choosing state j, Z_{ij} and α represent all the observed factors and their parameters obtained from the model.

In the first equality of the equation, the coefficient α_i differs across individuals. Like the MNL, the MMNL assumes that the error terms, ε_{ij} are IID. However, it relaxes the restriction that α is the same for each individual, allowing it to be stochastic instead.

The second equality in equation (1) expresses another way to look at the 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. Thus, the MMNL incorporates taste variations across individuals.

Through attributing each respondent to a random term, taste variations, unobserved heterogeneity in alternatives and unobserved heterogeneous choice sets are allowed (Bhat 2000B). For example, attributing to each patient a specific coefficient of *Price* for each alternative reflects both the patient's taste and sensitivity in unobserved heterogeneity in alternatives and their unobserved heterogeneous choice set.

The empirical issue is to compare their estimation performance. 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 authors, such as Horowitz (1980) and Van den Berg et al. (2010), argued that random unobserved heterogeneity in the marginal utilities does not bias MNL estimates. Carlsson (2003) and Dahlberg and Eklöf (2003) reached the same conclusion and indicated that there are no conflicting signs with the two models and that the magnitude of the coefficients are very close, with just a few exceptions.

By contrast, Bhat (1998, 2000A) found that WTP for all attributes are higher with the MMNL than with the MNL, indicating that the MNL underestimates WTP. Revelt and Train (1998) showed significant differences in WTP for some attributes while for others it showed none. Other researchers provided evidence that WTP is higher for some attributes but lower for others with the MMNL than with the MNL. Van den Berg et al. (2009) found that the MNL underestimates the WTP for travel time compared with the MMNL, but overestimates the WTP for other attributes. Train (1998) showed that the WTP is larger with the MMNL than with the MNL. However, the WTP from his MMNL with correlated marginal utilities is smaller than that with the MNL. He concluded that there is probably no general answer to whether or not the 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. Perrson (2002) 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 the MNL and the MMNL. The result from the former contradicts the fundamental laws implied in welfare economics that demand falls as price rises.

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

To conclude, the debate around the potential bias using the MNL in the case of preference heterogeneity is not yet closed. While few works (Harris and Keane, 1999; Borah, 2006; Canaviri, 2007; Hole, 2008; and Qian et al., 2009) have used the MMNL in health care demand studies, the econometric tests on the basis of rural Chinese patients with two samples of diverse demand heterogeneity offer a promising case and will provide new evidence on the relative performance between the two methods.

3. Estimation method and data

3.1. Model specification

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

$$U = U(h_i, x_i) \tag{2}$$

Health status, h, is determined by the quantity and quality of health care (C), other health inputs (e.g., sanitation) and food consumption (F); and individual attributes such as age, gender, education, state of insurance, and asset (R).

$$h_i = h(C_i, F_i, R_i) \tag{3}$$

Healthcare demand is a function of the price of health care (p) and the distance to the health care provider (D). The importance of D is that distance not only implies cost of access, but also reflects the reputation and quality of providers.[3]

$$C_i = C(p, D) \tag{4}$$

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

$$F_i = F(E_i) \tag{5}$$

With equations (2) to (5), we get the indirect utility function expressed in equation (6) in the case where individual i chooses health care provider j in which $y_i - p_j - E_i$ is the budget for non-health consumption (y is income).

$$V_j^* = U(h(C_j(p_j, D_j), F(E_i), R_i), y_i - p_j - E_i) \tag{6}$$

Among the health care provider alternatives, the patient will choose the one that maximizes his/her indirect utility function. The choice rule is expressed by equation (7).

$$V_j = 1, \text{ if } V_j^* = Max(V_1^*, V_2^* \ldots V_j^*)$$
$$V_j = 0, \text{ otherwise} \tag{7}$$

To make the model amenable to econometric estimation, we must define a functional form of the

[3] Large health care providers must be located in towns or cities. Consequently, their distance is farther than small health care providers in the proximity of rural villages. It could be argued that there is some correlation between the price and distance effects because to most villagers price and distance are two common factors of access to a big hospital. However, we argue that these effects are also clearly nuanced due to the difference in factors that cause these effects: while price effect is mainly determined by the evolution of a given individual's income and assets, the distance effect may be influenced to a larger extent by the evolution of aging.

above indirect utility function. This is expressed by equation (8) 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 appeared in equations (5) and (6) is now unobserved and is treated as one part of the error term.

$$V_j = V^*_j(p_{ij}, D_{ij}, y_i, R_i) + \varepsilon_{ij} \qquad (8)$$

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

$$V^*_j(.) = Z_{ij}\beta_z + X_i\beta_{xj} \qquad (9)$$

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

$$V_j = \alpha_j + \beta_1 p_{ij} + \beta_2 D_{ij} + \beta_{3j} y_i + \beta_{4j} R_i + \varepsilon_{ij} \qquad (10)$$

The variable p, the health care price, and D, the distance to health care 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 (10) is estimated with the 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 (9)), the result will be:

$$\boldsymbol{Prob(j)} = \frac{\exp(\alpha_j + \beta_j' \, x_{ij})}{\sum_{q=1}^{J} \exp(\alpha_q + \beta_q' \, x_{iq})} \qquad (11)$$

The difference between the MMNL and the MNL is that in the former, one part of the coefficients is random; in the latter, all coefficients are non-random. In equation (11), β'_j is composed of β_{ji} with

$$\beta_{ji} = \begin{cases} \beta_j + \sigma_j \eta_{ji} \; \textit{if random} \\ \beta_j' \;\; \textit{if non-random} \end{cases} \qquad (12)$$

where β_j is the population mean, η_{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 $f\beta_j$. The elements of β_{ji} are distributed randomly across individuals with fixed means.

We set both price and distance to health care 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 are more sensitive to price, they may care less about the distance; that is, they may accept less expensive but more distant providers. By contrast, when they are less sensitive to price, they may prefer a less distant provider.

If the random terms are normally distributed,

$$\beta_{ki} \sim Normal\left[\beta_k + \delta_k^{'} w_i, \sigma_k^2\right] \tag{13}$$

Equation (13) 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.

3.2. Data, variables and characteristics of the samples

Data are from the CHNS database edited by the Carolina Population Center (CPC, University of North Carolina). 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, 2006, 2009, and 2011).

The reasons we do not use the data after 2006 are two. First, rural exodus has been accelerating since 2009. According to 2009 survey, in rural area, around 40% of household members left home and worked in cities. Extending to 2009 may exacerbate the bias in comparisons. Second, health care reform could also affect demand heterogeneity. As health insurance reforms began in 2003 but took several years to implement and only reached a real impact after 2006, the obtained results could be interpreted as being impacted by insurance reforms.

We build two samples. Within each sample, income, health care prices and supply conditions were not meaningfully evolved, but between them these factors were substantially changed. The number of patients interviewed who were ill was smaller in the first waves than in the last (population aging appears to be the main cause). Thus, 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, for a total of 2,117 and 2,594 observations, respectively. The first sample included individuals under 18 years old as the following waves did not. We conducted a logistic regression analog of the Chow test to check whether the health care demand of the under-18 differed from that of the over-18 (see Demaris, 2004). Results showed that the two models indeed differed. Consequently, observations of individuals under 18 were removed. Finally, our samples included 1,457 rural individuals who reported having been ill in 1989, 1991 or 1993, and 2,594 individuals 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 twice. CHNS data collectors have not given more details on attrition. Nevertheless, as Deaton (1997) stated, the rate of refusal of participation is lower in developing countries. It must be still lower in rural China since political institutions exert strong control. Thus, we attribute lack of participation on the part of villagers to their physical absence, their moves or their deaths. Therefore, attrition can be regarded as random.

Table 1 presents all variables used and their definitions.

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-treatment (S)	=1 if treatment by self 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 otherwise.
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.

Notes: 1) data come from the CHNS database; 2) the first five items (*V*, *T*, *C*, *O*, *S*) concern the dependent variable spread in a selected set of health care providers; 3) all of the following variables concern the independent variables; 4) with the exception of the first five and the last three, all of the remaining variables are individual-specific attributes; 5) the last three variables were used to take into account environmental features; *Rural_popu_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; 6) *Asset* and *Pj* are built with the method described in section 3.2.

The CHNS database provides household per capita annual income at a constant price. As the impact of a household's income and assets on their health care provider choice can be quite different, we built an asset index and simultaneously used income and asset to measure income and wealth effects. Following several authors (Sahn and Stifel, 2000; Filmer and Kinnon, 2008), we used the 9 items, with 4 to 8 modalities for each, and then employed principal components analysis to derive weights (Filmer and Kinnon, 2008) for the asset index.[4]

We also wrestled with how to compensate for missing data on health care prices. The MMNL requires the prices of all alternative providers, while only the prices of the providers that the patients effectively visited were recorded in the survey. Thus, 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 descriptive statistics of actual plus imputed prices by type of provider are presented in Table 2.

Table 2 calls for some brief comments. First, comparing the two samples, income, asset, education level, health care price, the share of patients with insurance, and village size were meaningfully increased over time. 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 health care providers increased from 30% to 32% in favor of county hospitals (from 9% to 18%) and to the detriment of

[4] The coefficients of correlation between the obtained *Asset* and *Income* were 0.29 for both periods (1989-1993 and 2004-2006) and were significant at 1%.

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 15% reduction appears to have benefited self-treatment, which grew 14%.[5]

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 (V)	0.48	0.50	0	1	0.22	0.41	0	1
Town-C (T)	0.21	0.41	0	1	0.14	0.35	0	1
County-H (C)	0.09	0.29	0	1	0.18	0.39	0	1
Other-type (O)					0.11	0.32	0	1
Self-treatment (S)	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

[5] *Other_type* generally includes 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.

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

Notes: 1) data come from the CHNS database; 2) the first five items (*V*, *T*, *C*, *O*, *S*) concern the dependent variable spread in a selected set of health care providers; 3) all of the following variables concern the independent variables; 4) with the exception of the first five and the last three, all of the remaining variables are individual-specific attributes; 5) the last three variables were used to take into account environmental features;
Rural_popu_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; 6) *Asset* and *Pj* are built with the method described in section 3.2.

4. Estimation results

Tables 3 and 4 contain the regression results of the 1989-1993 and 2004-2006 data samples, respectively. The software used for both models is Nlogit. MMNL estimates are obtained with 100 Halton draws.

4.1. MNL versus MMNL

For both periods, the MMNL yields higher likelihood values and provides improved fits over the MNL (likelihood ratio test is significant at less than 0.01), indicating that the explanatory power of the mixed logit is greater than with the standard logit. 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 the AIC. According to the AIC, the MMNL is better while according to the BIC, the MNL is preferred. Thus, the results are not conclusive.

Assuming individual rationality, a negative price effect is expected. Table 3 shows that according to both models in 1989-1993, there were clear price effects. The estimated means are -0.377 (significant at 5%) and -1.606 (significant at 1%) for the MNL and the MMNL, respectively. 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) obtained similar results. According to the authors, 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

Notes: 1) data come from the CHNS database; 2) *Village-C*, *Town-C*, and *County-H* concern the dependent variable spread in a selected set of health care providers; 3) with the exception of the last three, all of the remaining explanatory variables are individual-specific attributes, and their definitions are made in Table 1; 4) the last three variables were used to take into account environmental features. *Rural_popu_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; 5) *Asset* and *Price* are built with the method described in section 3.2; 6) 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 (0.510)**	-1.351 (0.576)**	-1.239 (0.551)**	-1.114 (0.639)*	-1.073 (0.514)**	-1.449 (0.619)**	-1.283 (0.626)**	-1.260 (0.680)*
Age	-0.0005 (0.005)	-0.006 (0.006)	-0.015 (0.005)***	-0.010 (0.006)*	-0.001 (0.005)	-0.006 (0.006)	-0.016 (0.006)***	-0.010 (0.006)*
Edu_level	-0.057 (0.066)	-0.116 (0.073)	-0.101 (0.064)	-0.075 (0.075)	-0.057 (0.067)	-0.119 (0.078)	-0.106 (0.072)	-0.066 (0.078)
Women	0.083 (0.127)	-0.051 (0.142)	-0.038 (0.133)	-0.098 (0.150)	0.083 (0.128)	-0.059 (0.151)	-0.050 (0.150)	-0.091 (0.157)
Hhsize	-0.007 (0.039)	0.009 (0.044)	-0.015 (0.041)	-0.113 (0.049)**	-0.007 (0.039)	0.010 (0.046)	-0.014 (0.046)	-0.125 (0.051)**
Asset	-0.143 (0.092)	0.089 (0.103)	0.202 (0.092)**	0.059 (0.110)	-0.142 (0.092)	0.085 (0.110)	0.241 (0.104)**	0.086 (0.116)
Income	-0.004 (0.009)	-0.005 (0.011)	-0.003 (0.009)	-0.011 (0.012)	-0.002 (0.008)	-0.008 (0.012)	-0.002 (0.010)	-0.012 (0.013)
Severity	0.388 (0.095)***	0.930 (0.103)***	1.124 (0.098)***	0.621 (0.112)***	0.406 (0.097)***	1.042 (0.115)***	1.252 (0.118)***	0.678 (0.119)***
Marital	0.068 (0.151)	0.135 (0.174)	0.281 (0.164)*	0.154 (0.182)	0.076 (0.153)	0.148 (0.186)	0.376 (0.184)**	0.177 (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	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(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			

Notes: 1) data come from the CHNS database; 2) *Village-C*, *Town-C*, *County-H*, and *Other-Type* concern the dependent variable spread in a selected set of health care providers; 3) with the exception of the last three, all of the remaining explanatory variables are individual-specific attributes, and their definitions are made in Table 1; 4) the last three variables were used to take into account environmental features. *Rural_popu_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; 5) *Asset* and *Price* are built with the method described in section 3.2; 6) 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 with the MMNL, price effect disappeared with the MNL. As shown in Table 4, the coefficient of *Price* is 0.01 and is no longer significant. Nevertheless, in the MMNL model, price effect was present with a coefficient of -0.409 (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.

To reinforce the judgment that the MNL is biased, one way to compare the relevance of the MMNL and the MNL is to use their estimated coefficients of *Price* to compute the WTP for illness severity. As severity is classified into three degrees, the WTP for severity can be interpreted as the amount patients are willing to pay for one (more) degree of severity. From Table 5, it appears that the results with the 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 patients, the WTP increase for severity seems reasonable. The WTP with the MNL for 2004-2006 is not presented due to the absence of a significant price effect, leading the derived WTP unreliable.

Table 5. 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

Notes: 1) data come from the CHNS database; 2) the estimated coefficients of *Price* with the MNL and MMNL are used to compute the WTP for illness severity. This is calculated as the coefficient of *Severity* divided by the coefficient of *Price* in absolute value; 3) *Price* is built with the method described in section 3.2, and their coefficients are found in Tables 3 and 4;

The second random variable is distance to health care provider. In accordance with the analysis on price effect, the coefficients of *Distances* with the MMNL are higher than with the MNL. However, unlike the 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 all else being equal, patients prefer closer over farther health care providers. In 1989-1993, *Distance1* is insignificant in both the MMNL and the MNL. In 2004-2006, nevertheless, all Distance dummies are significantly negative, indicating that distant health care providers are less likely to be chosen.

One interesting question is while the MNL fails in estimating price effect, why does it succeed in estimating distance effect in the second period? This is a logical consequence of the difference in the degree of heterogeneity. The MNL fails to estimate price effect because the heterogeneity of the price effects on preference has increased. Nevertheless, as will be shown in Table 6, heterogeneity in distance effects was either unchanged (with *Distance2*) or decreased (with *Distance1* and *Distance3*) in 2004-2006. Therefore, the MNL succeeds in estimating the 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: the MNL fails to provide good estimation when heterogeneity is high.

Another comparison is the quantity of information contained in the two models. The MMNL makes more information available than the MNL in that it estimates the extent to which patients differ in their provider preferences. Unobserved heterogeneity is represented by the standard deviation parameters. In an 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.

4.2. The importance of heterogeneity analysis in interpreting price and distance effects

Given that the variables other than price and distance are patient-specific and do not vary by health care provider, they cannot be assigned with a random term; their coefficients with the MMNL and the MNL are similar in sign and extent. As their interpretations are out of the scope of either study on heterogeneity or comparison between the MMNL and the MNL, we choose to show them without comments.

The MMNL provides information on the heterogeneity of provider choice in price and distance. In Tables 3 and 4, the standard deviations of price parameters are 2.1 and 1.375 for the two samples, respectively and both are significant at 1%, indicating that parameters indeed vary in the population. Following equation (13), 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; the result is presented in Table 6. In 1989-1993, while about 80 % of patients followed the rule that when the price rises, the demand falls, it is not observed for 20% of patients. That percentage rose to 38.30% in 2004-2006, indicating that heterogeneity in price preferences meaningfully increased in the second period. Meanwhile, whereas heterogeneity in *Distance2* was unchanged, both *Distance1* and *Distance3* have decreased (from 45.03% to 26%, and 13.59% to 8.92%, respectively).

Table 6. Heterogeneity measured by percentage of patients of which the coefficients of Price or Distances >0.

	1989-1993	2004-2006
Price	22.22%	38.30%
Distance1	45.03%	26.00%
Distance2	26.73%	26.86%
Distance3	13.59%	8.92%

Notes: 1) data come from the CHNS database; 2) *Price* and *Distances* are built with the method described in section 3.2, and their coefficients are found in Tables 3 and 4; 3) Calculated with equation (13) and using the mean coefficients and SD of parameter distributions from Tables 3 and 4.

It is time to explain why the information on choice heterogeneity has crucial importance for our study on price and distance effects, and to what extent the provision of this information allows us to avoid a biased image of these effects. Arguments are summarized in Table 7.

Table 7. Influence of income growth and population aging on price and distance effects

	Price effect		Distance effect	
	Mean level	**Heterogeneity level**	**Mean level**	**Heterogeneity level**
Income growth	↓	↑	↓	↑
Aging	↓	↓	↑	↓

Source: authors.

We have two samples with key differences in income and aging, and want to estimate the changes in price and distance effects. Firstly, look at the third line. By deduction, due to the increase in income, mean price effect should be weaker, because people must have higher financial ability to afford health care. The heterogeneity in choice tends to be greater, because increasing income provides more choices and allows for greater consideration of health care quality. Higher income could also reduce mean distance effect because of higher transport access ability. Like in the case of price effect, income growth tends to increase the heterogeneity in distance effect, because this heterogeneity is highly correlated with the heterogeneity level of the price effect due to income growth: in general, people accepting higher prices also accept to travel longer distance for better health care, leading to more various choices in distance among the total population. With these raisons, income growth causes the same changes for price and distance effects in terms of the mean and heterogeneity levels.

Here an important variant that is not illustrated in the table is the difference in income inequality: In the case of high inequality, as the effect of price and distance is high for the poor, and their choices are more homogenous, the mean effect for both price and distance will be higher than in the case of low inequality. Its heterogeneity levels will also be lower than in the case of low inequality due to the high homogeneity in choice of the poor.

Secondly, look at the fourth line. Aging would be expected to decrease the mean price effect because elderly people in poorer health have less freedom to choose according to price. Coordinately, the heterogeneity in price effect also decreases. Aging would be expected to increase the distance effect due to the stronger preference of aging people for provider proximity. Coordinately, there is an increasing homogeneity of this preference.

Now, we use the arguments summarized in Table 7 on the basis of our two-sample case to evaluate the price effect for judging the feasibility of allocating more health care resources in the high-quality and high-cost health care infrastructure. Comparing the absolute levels of the coefficients of *Price* between two periods in Tables 3 and 4, we observe a significant decrease of the mean price effect (from -1.606 to -0.409).[6] With this decrease, the appealing policy would be to allocate more resources to high quality services.

However, without checking the heterogeneity level, this policy implication could be problematic. The coefficients of variation (SD/mean), indeed, rise from 1.3 to 3.2, but, as indicated in Table 6, the percentage of patients who followed the rule that demand falls as price rises only decreased from 77.8% to 61.7%. These indicators on heterogeneity suggest the existence of a majority of patients with modest incomes and imply a persistent need to lower the price of services. In this case, the policy aiming to favor high- and high quality services would be erroneous.

Assume now an evaluation of distance effect for the purpose of a geographical allocation of health care resources. In general, a weaker mean distance effect suggests a more geographically concentrated distribution (focusing on several modern and large hospitals to serve the distant population). By contrast, the high mean distance effect indicates a demand for proximity and hence a geographically more decentralized structure. According to the column 4 in Table 7, income growth and aging oppositely affect the mean level of the distance effect. Hence, the distance effect depends on which force: income growth or aging, is more prevalent. Merely focusing on mean effect would likely lead to a biased policy.

If the influence of income growth is higher than aging, the mean distance effect becomes weaker and the concentration solution with more large hospitals could be a relevant answer, because traveling for a longer distance matters less. But it could be wrong if income inequality becomes high.

In the case where the influence of income growth and aging are equal so that the mean levels of distance effects are the same, the evolution of the mean levels would be unable to give any insight in the necessary direction of policy change. In such a case, knowing the heterogeneity level and being able to statistically identify the sources of the heterogeneity make identifying appropriate solutions possible. For instance, if low heterogeneity of the distance effect is caused either by aging or by income inequality (with more "poor"), the most efficient solution would be to fund more local small health care structures. On the contrary, if high heterogeneity is caused by increasing preferences in quality, concentrating on a solution that provides large and modern hearth care structures would be efficient.

In our two-sample case, the mean distance effect has increased with the measurements of small and middle-level distances, but it decreases with the largest distance (*Distance3*).[7] This result merely based on mean effects could be difficult to interpret for policy making purposes. As the result provides information on a lower level of heterogeneity, according to the columns 4 and 5 in

[6] This direct comparison of the coefficients can be endorsed with two arguments: 1) the health care prices have been converted to comparable constant prices for both samples; 2) the direction of change of the coefficients is in line with the theoretical deduction illustrated in Table 7: both income growth and aging lead price effects to decrease.

[7] The coefficients of *Distances* between two samples are comparable, because the unit of measurement is the same: kilometer.

Table 7, we can conclude that the main cause of the evolution of mean distance effect and reducing heterogeneity is due to patient aging, and implies the need for more decentralized small structures to satisfy the increasing aging population.

4.3. Policy implications

These analyses on the role of demand heterogeneity seem to be quite pertinent to explaining what has been happening in China for more than twenty years: due to extraordinary economic growth and a rising demand in health care, the public health expenditure has focused on large hospitals located in cities at the expense of the smaller ones. There is a growing defiance and dissatisfaction on the part of patients, due to the mediocre quality of health care in small and middle-sized public facilities. This disequilibrium may not be remedied even with increasingly efficient medical insurance (Petitfour, Huang, Audibert, Mathonnat, 2017). The Chinese government is facing the challenge of rethinking their health care reform.

Two specific policy orientations taken by Chinese government seem that it has been progressively taking into account the concern expressed theoretically in this paper.

First, the geographical mapping of health facilities must take account of the heterogeneity of demand which militates in favor of the development of local/proximity health facilities. This is implicitly the way in which the Chinese authorities have engaged since President Hu Jintao announced, according to a decision of the Politburo of October 2006, that everyone should have access to affordable basic health care. The movement accelerated with the adoption of the April 2009 reform which promoted the development of township hospitals and village health stations in terms of capacity and quality of care. But there is still a long road ahead before they are sufficiently attractive.

Second, if patients are allowed to behave according to the heterogeneity of their preferences, the package of benefits covered by the New Cooperative Medical Schemes must be made transferable between the health care facilities of the same level, so that patients are not obliged to attend those which are in the area of which they are administratively dependent. This is already the case for many NCMS and the trend is accelerating. It would also have the advantage of fostering healthy competition between structures of the same level.

In addition, the new set of reforms adopted in 2013 following the 18th Central Committee of the Communist Party, which gives a strong impulse to market mechanisms and private providers in the financing and regulation of hospitals and insurance, raise both opportunities and challenges to better take into consideration the heterogeneity of demand in the behavior of patients.

5. Conclusions

We constructed two samples surveyed within the same regions but with an interval of 18 years. We assumed that due to general income growth and population aging, there would be considerable evolution in patients' choices and that these choices would increase in heterogeneity. We applied both the MMNL model and the MNL model with exactly the same variables for testing the evolution of price and distance effects on health care provider choices.

As expected, we found that over the two periods, mainly due to income increase and aging, the price effect became weaker and more heterogeneous; the distance effect became stronger and less heterogeneous. Two main conclusions emerge from these key findings.

From a methodological perspective, we found that in both periods, the MMNL provides improved fits over the MNL. In 1989-1993, both the MNL and the MMNL models identified clear effects on patient provider choices. However, in 2004-2006, unlike with the MMNL in which price effect exists but is weakened, price effect disappeared with the MNL. We concluded that the failure of the MNL model to predict weaker but existing price effects can be attributed to its inability to deal with heterogeneity, thereby leading to a biased estimate. These results suggest that, in the presence of important individual preference heterogeneity, researchers should be cautious when interpreting the estimation results produced with the MNL model and that the MMNL model is the most suitable to study health care demand.

For health policy design and implementation, we have illustrated the crucial importance of the information on heterogeneity levels of price and distance effects for the sake of policy making. If only the evolution of the mean price effect is taken into account, health care resource allocation risks being biased towards high-quality and high-cost- health care supplies at the expense of basic needs-oriented services required by a majority of patients affected by aging and income inequality. Geographical allocation of health care resources just on the basis of the mean distance effect could also be erroneous because the influences of income growth and aging on mean distance effects go in opposite directions, and only the evolution of the heterogeneity level over distance effect allows policy makers to get a comprehensive picture of the situation.

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