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The choice of medical providers in rural Bénin: a comparison of discrete choice models [1]

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Abstract

In this paper we estimate three different discrete choice models of provider choice using data from the rural District of Ouidah in Bénin. These three model are: Multinomial Logit (ML); (2) Independent Multinomial Probit (IMP); (3) Multinomial Probit (MP). A comparison of IMP and MP allows us to reject the independence assumption between providers. Furthermore, the cross-price elasticities computed from the restrictive specifications (ML and IMP) are dramatically different from those computed from the more general one (MP). These results cast some doubt on the validity of the previous findings and policy recommendations that are typically based on the ML specification.

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1. Introduction

It is usually acknowledged that a high level of literacy and generalized good health are sine qua non conditions to durable development. This is why so many developing countries have until recently heavily subsidized their health care system. The financial crisis of the 1980s has forced some to consider instituting some form of user fees. Many fear such fees may drive individuals living in rural communities away from institutional health systems towards traditional, less efficient, health care. Proponents of user fees argue that fees allow the recovery of operating costs and increase the allocative efficiency, as long as they are set at the marginal cost of providing the health services. Opponents, on the other hand, claim that the impact of introducing fees will be unequally distributed across income classes.

It is well known that even in absence of user fees, access to the health services is not equal due to non-monetary factors such as travel time (Acton, 1975). Much of the recent empirical research has thus been concerned with studying the impact of price and non-price rationing on the demand for health care. The literature has given rise to two conflicting sets of results. On one hand some studies find the demand for health care to be relatively insensitive to price and travel time (Akin et al., 1984, 1986; Heller, 1982; Lacroix and Alihonou, 1992), while on the other hand as many studies find the opposite (Dor et al., 1987; Gertler et al., 1987; Gertler and van der Gaag, 1990; Mwabu, 1986; Mwabu et al., 1993).

Arguably, these conflicting results can arise due to numerous reasons. First, the data used by these authors concern different countries and different years. Second, while the majority of papers address the static conditional decision of provider choice (e.g., Gertler et al., 1987; Mwabu et al., 1993), others model the frequency of visits at a given provider over a certain time horizon (e.g., Lacroix and Alihonou, 1992; Heller, 1982; Lavy and Quigley, 1993). Finally, all datasets lack some important variables (e.g., opportunity cost of time, price of treatment, etc.) that may seriously affect the parameter estimates.

Nearly all the papers that concentrate on provider choice utilize the multinomial logit specification (ML), or the less restrictive nested multinomial logit specification (NML) [2]. Yet, it is well known that the ML imposes severe constraints on individual behavior. Since most policy recommendations are based on this specification, it is worth investigating whether it is consistent with more flexible ones. In this paper we estimate a model of provider choice using different statistical specifications. After estimating the widely used ML model, we estimate an

[2] The ML is often not rejected by the NML (see, e.g., Gertler, 1987).

independent probit model (IMP). Although restrictive, this specification does not suffer from the well-know independence of irrelevant alternatives (IIA) that plagues the ML model. Finally, we estimate a multinominal probit model (MP). The main impediment to widespread use of the MP model is that the estimation of the choice probabilities is very cumbersome and time consuming. Recent contributions have nevertheless made this model relatively easy to estimate. We are not aware of any attempt to estimate a provider choice model using this specification. Our estimation strategy consists in comparing the own and cross-price elasticities estimated with these different statistical specifications.

A second goal pursued in this paper is to investigate the role played by informal saving on provider choice. Informal credit systems, also know as "tontine" in French-speaking Africa, is often the only source of saving in rural areas. All the aforementioned studies have overlooked this crucial aspect of health care demand in developing countries. Indeed, the manner in which individuals finance their health care consumption has been completely neglected from the empirical and theoretical analyses. Traditionally, most authors have simply considered health care consumption as equivalent to any other good. Yet, given that future spells of illness (caused for example by parasitic diseases) will occur with a given probability, individuals can protect themselves by saving a fraction of their income for precautionary purposes.

In order to incorporate saving into the model, we must turn to a two-period model of utility maximization within an uncertain environment. Proper modeling requires the specification of both a utility function and a health production function. The econometric implementation of such a model is made complex by the stochastic interdependence between the discrete decision of provider choice and saving. Furthermore, the data required to estimate the model are such that virtually no dataset exists that contain all the necessary information.

We thus follow Cameron et al. (1988) and use the economic model as a basis for specifying a linearized version of the structural model of provider choice. The endogenous saving variable is instrumented and used as an exogenous covariate. The data we use come from an experiment on primary health care that is being conducted in the District of Ouidah in the République du Bénin. The experiment consists essentially in decentralizing the health services from the district level to the community level. There are 9 communities in the District of Ouidah. Each community is made up of three or four villages and offers the same type of health care through a single community health center (CHC). The fees currently charged by the CHCs do not recover operating costs. The CHCs are thus heavily subsidized by international organizations and pressure is being exerted to increase the fees. It is therefore relevant to investigate the sensitivity of the demand for primary health care and to simulate the impact of increasing the fees at various providers.

In the next section we present the theoretical model. Section 3 presents the econometric models. The data and the institutional environment of the experiment are discussed in Section 4. In Section 5, the results are presented and discussed. Finally, we conclude in Section 6.

2. The economic model

Most empirical papers on health care demand are framed within a one-period model. The theoretical model simply specifies that, conditional on being sick, the individual must decide how to allocate his income between consumption and health care. Yet, to the extent a spell of disease will occur with a given probability, an individual may protect himself by saving a fraction of his income. Naturally, the introduction of saving into the model complicates matters significantly. Indeed, the individual's decision must be cast within a two-period model with uncertainty.

Consider a world in which there are only two periods. Following Cameron et al. (1988), Lavy and Quigley (1993), we assume that consumers derive utility from their health, H, measured in income equivalent, and consumption in period i, C_i $(i = 1, 2)$: $U = U(C_1, C_2, H(Q, n; \mathbf{A}))$. The health production function depends on health services, Q, and health status, n, conditional on a vector of exogenous factors, $\mathbf{A}$ (age, health capital, ...) [3]. The utility function and the health production function are assumed increasing in each argument.

The individual can transfer income between periods through saving, S. In the first period, he must thus allocate his exogenous income between consumption and saving. Uncertainty arises in the model because when the saving decision is made in the first period, the health status that will prevail in the next is not known. Individuals have a prior probability measure of health states given by $\pi = \pi(n; \mathbf{B})$, where $\mathbf{B}$ includes individual characteristics and environmental variables such as access to running water, etc.

To simplify the model, we will assume there are a limited number of services available to the individual. These levels correspond to the number of different available providers, J, say. Expenditures on health care will thus depend on the type of care, Q_j, conditional on the exogenous factors, $\mathbf{A}$: $E_j = E(Q_j; \mathbf{A})$. In a competitive market, the expenditure function represents the envelope of consumers' bid for different types of treatments, given the distribution of $\mathbf{A}$. Under these assumptions, the individual must solve the following program:

$$\underset{j, C_1, C_2, S}{MAX}\ EU_j = \int_n U\big(C_1, C_2, H(Q_j, n; \boldsymbol{A})\big)\, d\pi(n; \boldsymbol{B}) \tag{2.1}$$

[3] Strictly speaking, health capital and past health states should be incorporated into the model. This would lend the model interesting dynamic properties. Unfortunately, our data contain no information on past events. We are thus constrained to consider these as exogenous in the model.

subject to

$$C_1(n) + S(n) = \gamma_1 \; C_2(n) + E_j(n) = \gamma_2 + (1+r)S(n) \tag{2.2}$$

where r is the interest rate and Y_i is the exogenous income in period i. The price of consumption is assumed the same in each period and is normalized to unity. The first budget constraint states that the first-period income must be allocated between consumption and saving. The second constraint states that the second-period income plus saving and interest must be allocated between consumption and expenditures on health care.

In principle, one could specify a particular functional form for the utility and health production functions and solve the above program. Indeed, conditional on provider j and each possible realization of n, one could obtain demand equations for C_1, C_2 and S. These could then be substituted back into Eq. (2.1). Integration over n would yield expected indirect utility functions, EV_j, say. These functions would form the basis for the analysis of provider choice, with j chosen to maximize EV_j.

The main difficulty with such an approach is that it is very difficult to find functional forms for the utility and health production functions that yield closed-form solutions for the endogenous variables. Even if such solutions exist, it is not clear that upon substitution in Eq. (2.1) the expected indirect utility would have a tractable form when the integration over n is performed [4].

As mentioned previously, one of the objective of this paper is to estimate a model of provider choice that takes consistently into account the possibility that some individuals save part of their income in order to protect themselves against future spells of illness. The simple theoretical model sketched above highlights the fact that saving and provider choice are linked decisions. Indeed, it can be shown under general assumptions that if the probability of a bad state of nature increases (thereby decreasing $H(\cdot)$), saving in the first period will increase in order to allow better treatment (higher Q_j) in the second period. This raises the possibility that individuals who save more have unobservable characteristics that increase the probability of such bad states. To account for the endogeneity of saving, we must instrument this variable in the provider choice model. The estimation strategy consists in instrumenting saving in a first step based on the above theoretical model. In the second step, we estimate a discrete model of provider choice based on predicted saving. To ease the econometric estimation of the model, we will assume that the expected indirect utility function is linear in parameters.

[4] Cameron et al. (1988) show in a similar model that if the utility and health production functions are Cobb–Douglass, the demand functions will be analogous to the linear expenditure system. The price to pay in this case is to assume that the preferences are homothetic. Still, substituting the demand functions back into the direct utility function yields a highly non-linear expected indirect utility function that must be linearized to allow econometric estimation.

3. Model estimation

3.1. Utility function

Following the above discussion, we assume that ill individuals maximize a quasi-indirect conditional utility function:

$$V_{ij} = V_{ij}(y_i, E_{ij}, S_i, \boldsymbol{P}; \boldsymbol{A}_i) \tag{3.1}$$

where y_i is a measure of income, E_{ij} is the health expenditure at provider j, S_i is saving, $\mathbf{P}$ is the vector of prices of other goods and $\mathbf{A}_i$ is as defined previously. The utilization of such an indirect utility function implicitly assumes that C_1 and C_2 are solved conditionally on S. Upon substitution in the direct utility function, the quasi-indirect utility function depends on income, expenditures at provider j, other prices and saving. It thus allows direct investigation of the impact of saving on provider choice. From the econometric point of view, S must be instrumented to avoid biasing the parameter estimates.

The quasi-indirect utility function has some implications on the underlying structure of preferences. First, it implicitly assumes the direct utility function is additively separable between C_1 and C_2. Second, by solving Eq. (3.1), one gets health care consumption rather than "health status improvement". This undesirable feature is mitigated by the fact that the health status is directly related to health care consumption through a health production function.

For empirical implementation, the vector $\mathbf{P}$ is normalized to unity. This is justified on the ground that our data come from a narrowly defined geographical area and depicts very little variation across communes. Furthermore, we append an error term to Eq. (3.1) to make the model amenable to econometric estimation. More specifically, we write:

$$V_{ij} = V_{ij}^*(y_i, E_{ij}, S_i; \boldsymbol{A}_i) + \epsilon_{ij} \tag{3.2}$$

where $V_{ij}^*(\cdot)$ is the deterministic component of utility and ϵ_{ij} is a disturbance term. The quasi-indirect utility function in Eq. (3.2) must be parameterized to allow estimation. We follow the majority of papers in the literature and rewrite the systematic component as:

$$V_{ij}^*(\cdot) = \boldsymbol{Z}_{ij}\beta + \boldsymbol{X}_i\gamma_j \tag{3.3}$$

The vector $\mathbf{Z}_{ij}$ includes the provider-specific attributes, such as the expenditure the individual must pay for treatment and the time required to receive treatment. The vector $\mathbf{X}_i$ comprises individual-specific attributes such as age, sex, income, etc. The systematic component is linear in parameters. This is necessary to ease econometric estimation. The quasi-indirect utility function obviously does not stem from a given direct utility function, but must rather be considered as a first-order approximation to a well-behaved one. This is the usual strategy used in the empirical literature on provider choice.

In our data we do not observe provider-specific attributes such as the number and types of available drugs or quality of staff. These unobservables are captured in the error term, ϵ_{ij}. Three assumptions regarding the distribution of the error terms can be postulated, each yielding a particular statistical specification.

3.2. Multinominal logit

The individual is assumed to know all the provider-specific attributes and to choose the one that maximizes his indirect utility. As is well-known in the discrete choice literature, the observed choice is determined by the difference in utility, not with the levels of utility per se. In other words, for identification purposes the parameters of one alternative must be normalized. Following the convention, we choose alternative J. Hence, subtract from the utility of each alternative j the utility associated with alternative J:

$$\begin{aligned} \nu_{i1} &= V_{i1} - V_{iJ} = (\boldsymbol{Z}_{i1} - \boldsymbol{Z}_{iJ})\beta + X_i(\gamma_1 - \gamma_J) + \epsilon_{i1} - \epsilon_{iJ} \\ \nu_{i2} &= V_{i2} - V_{iJ} = (\boldsymbol{Z}_{i2} - \boldsymbol{Z}_{iJ})\beta + \boldsymbol{X}_i(\gamma_2 - \gamma_J) + \epsilon_{i2} - \epsilon_{iJ} \\ \nu_{iJ-1} &= V_{iJ-1} - V_{iJ} = (\boldsymbol{Z}_{iJ-1} - \boldsymbol{Z}_{iJ})\beta + \boldsymbol{X}_i(\gamma_{J-1} - \gamma_J) + \epsilon_{iJ-1} - \epsilon_{iJ} \end{aligned} \tag{3.4}$$

For simplicity, rewrite these equations as:

$$\begin{aligned} \nu_{i1} &= \overline{\boldsymbol{Z}}_{i1}\beta + \boldsymbol{X}_i\bar{\gamma}_1 + \bar{\epsilon}_{i1} \\ \nu_{i2} &= \overline{\boldsymbol{Z}}_{i2}\beta + \boldsymbol{X}_i\bar{\gamma}_2 + \bar{\epsilon}_{i2} \\ \nu_{iK} &= \overline{\boldsymbol{Z}}_{iK}\beta + \boldsymbol{X}_i\bar{\gamma}_K + \bar{\epsilon}_{iK} \end{aligned} \tag{3.5}$$

where K = J − 1. The ML specification results if we assume the ϵ_{ij} are identically and independently distributed with Type I extreme value density functions. The probability that individual i chooses alternative j ($j \in \{1, \dots, K\}$) can be shown to be given by:

$$P_{ij} = \frac{\exp\left(\overline{\boldsymbol{Z}}_{ij}\beta + \boldsymbol{X}_i\bar{\gamma}_j\right)}{\sum_{l=1}^{K}\exp\left(\overline{\boldsymbol{Z}}_{il}\beta + \boldsymbol{X}_i\bar{\gamma}_l\right)} \tag{3.6}$$

The main advantage of this specification is its ease of computation. Indeed, the probability of choosing provider j is a closed-form equation of the sample data. This explains why this model has been used so frequently in the empirical literature. The main drawback of this model is that it imposes the so-called property of "independence of irrelevant alternatives". This property is a consequence of the implied assumption of no correlation between the error terms. Indeed, it is readily seen that the odds ratio between any two alternatives, say P_{ij}/P_{ik}, takes the form $\exp(\overline{\boldsymbol{Z}}_{ij}\beta + \boldsymbol{X}_i\bar{\gamma}_j)/\exp(\overline{\boldsymbol{Z}}_{ik}\beta + \boldsymbol{X}_i\bar{\gamma}_k)$, which is independent of the characteristics or even the existence of any alternative other than j and

k. As a result, it imposes a very restrictive pattern on the elasticities of P_{ij} with respect to the characteristics of alternative k, $\overline{Z}_{ik}$. Indeed, it can easily be shown that this elasticity will depend only on the characteristics of alternative k and not on those of alternative j! Similarly, if a new alternative is introduced in the choice set, all the selection probabilities will be reduced proportionately.

3.3. Independent multinominal probit model

The IMP specification, as the ML, imposes stochastic independence between alternatives. It simply assumes that the ϵ_{ij} are identically and independently distributed normal random variables. The probability individual i chooses alternative K, say, is given by:

$$P_{iK} = \int_{-\infty}^{\infty} \prod_{l=1}^{K-1} \Phi\left[\left(\overline{Z}_{il} - \overline{Z}_{iK} \right) \beta + X_i (\overline{\gamma}_l - \overline{\gamma}_K) + \epsilon_{iK} \right] \phi(\epsilon_{iK}) \, d\epsilon_{iK} \qquad (3.7)$$

where Φ is the standard normal distribution function and $\phi(\cdot)$ is the standard normal density function. Similar expressions can be derived for the other alternatives. This specification is still restrictive since it does impose the error terms to be independent. On the other hand, it can be shown that the cross-price elasticities are not constrained to be equal as in the ML specification.

3.4. Multinominal probit

The multinominal probit specification provides the most general framework to study discrete choice models since it allows correlation between all alternatives. This specification results if we assume that the ϵ_{ij} are identically normally distributed with covariance matrix Ω. The probability of observing an individual choosing alternative K is given by:

$$P_{iK} = \int_{-\infty}^{A_1} \int_{-\infty}^{A_2} \cdots \int_{-\infty}^{A_{K-1}} \psi(U; \Sigma) \, dU \qquad (3.8)$$

where $A_j = (\overline{Z}_{ij} - \overline{Z}_{iK})\beta + X_i(\overline{\gamma}_j - \overline{\gamma}_K)$, U is a $(K \times 1)$ zero mean vector, $\psi(\cdot)$ is a multivariate normal density function and Σ is the covariance matrix of the different error terms in Eq. (3.4). The main impediment to the use of this specification is the dimensionality of the response probabilities. Recent solutions to the dimensionality problem have been proposed by McFadden (1989) and Pakes and Pollard (1989). In essence, the multi-fold normal integral is replaced by a smooth (asymptotically) unbiased efficient simulator computed from an underlying latent variable model [5]. Using these probability simulators in a standard maximum likelihood framework is known as simulated maximum likelihood (SML) ap-

[5] In practice we use the so-called Geweke–Hajivassiliou–Keane (GHK) simulator, which has been shown to be very accurate (see Hajivassiliou et al., 1991).

proach. The asymptotic properties of this estimator have been studied by Pakes and Pollard (1989) and Lee (1992). We follow this procedure in this paper [6].

4. Data and institutional environment

4.1. The Pahou experiment

The République du Bénin is a small mainly rural country located in the Gulf of Guinea with a population of approximately 4.6 million inhabitants. It is considered one of the poorest countries of Africa with an annual per capita income of US 340 $ in 1988. Agriculture is the mainstay of the economy, employing three-fourths of the active population and accounting directly for 40% of the GDP and about 50% of foreign exchange earnings. The level of literacy is low by African standards; 37% for males and 16% for females. The health status of the population is also among the poorest in Africa. Infectious and parasitic diseases, trauma and nutritional disorders account for the high level of morbidity and mortality. Life expectancy at birth is only 56 years (in 1986) and infant mortality rate is 89.0 per thousand (down from 156, 5 years ago).

In seeking solutions to its health problems, the government of Bénin has adopted the so-called Alma Ata resolutions on primary health care. These essentially call for affordable access to basic curative and preventive care such as immunization against infectious diseases, prevention of endemic diseases, treatment of injuries, provision of essential drugs, etc. Prior to implementing nationwide programs, it was decided to experiment certain strategies on a small scale and to proceed to periodic evaluations.

In 1983, the Communes of Pahou and Avlékété, 25 km south–west of Cotonou, were chosen to implement different strategies since they constitute a microcosm of the country's demographic and geographic characteristics. A communal health centre (CHC) was erected in one of the villages to oversee the implementation of the various strategies and to centralize health services that could not be offered at the village level [7]. The main feature of the health policy that was implemented in 1983 and adhered to ever since consists in decentralizing the financing of the health services at the village level as well as the determination of the health services.

Since 1990, the experiment has been extended to the whole District of Ouidah, which comprises approximately 70 000 individuals. The district encompasses 9 communes, including those of Pahou and Avlékété. In each commune a health center similar to the CHC is available. Prior to extending the experiment, the

[6] See Bolduc (1994) for details.

[7] The health center is known as CREDESA — Centre Régional pour le Développement et la Santé.

CHCs were heavily subsidized by the central government. Each one now has to finance a large share of its operating costs through user fees.

As of 1992, it was decided to conduct a random survey covering the whole district of Ouidah in order to analyze the demand behavior with respect to primary health care. The sampling scheme was developed by statisticians from INSAE (Institut National de Statistique et d'Analyse Économique). The sample size was determined according to the following rule. A typical household comprises approximately 5 individuals. Previous surveys indicated that, on average, each individual is likely to experience two spells of fever (the most common reason for consulting) per year. Since the survey concerned the two weeks preceding the interview, it was necessary to visit approximately 2500 households in order to reach 1000 spells in the sample.

The survey we use was conducted between the months of May and September 1992. As many as 2591 households were visited by trained investigators. Overall these households represent 11502 individuals or nearly 16% of the total population. The average household size being 4.44, 880 individuals reported having suffered an illness during that period, rather than the expected 1000. There are very few indicators available to verify the representativeness of our sample. The last full-scale census was conducted in 1979 (INSAE, 1987) and published statistics are limited to provincial aggregates. To the extent the District of Ouidah is representative of the "Province de l'Atlantique", it might be worthwhile to compare our sample characteristics with those of the 1979 census. First, according to the census, women represent 51.6% of the total population of the province. In our sample, they represent 52.5% of all individuals. Second, as many as 66% of the population reported having no schooling at all. In our sample, this proportion is 64.7%. Finally, the census reports the marital status of individuals aged 13 and over, for men and women separately. Below we report the figures for both sources of data. Overall, our sample matches rather closely the figures of the census, despite the fact that it concerns a different period and a narrower geographic area. It is thus probably fair to say that our sample is representative of the population of the District of Ouidah.

Marital status, individuals aged 13 and over (%)

	Census (1979)		Sample (1992)	
	Men	Women	Men	Women
Single	36.1	13.9	40.4	21.4
Married	58.9	72.7	53.6	59.2
Widow	2.4	11.7	2.2	15.1
Divorced	2.6	1.7	3.7	4.2

Since the focus of the paper is on primary health care, visits pertaining to obstetric care were discarded. Upon deleting incomplete records, 796 observations

Table 1
Mean and standard error of selected variables

Variable	Total	Hospital CSSP	CHC	Private clinic	Self-treatment
Observations	796	52	253	139	352
Age	26.70	32.48	24.00	22.88	29.29
	(24.50)	(23.23)	(24.16)	(22.94)	(25.15)
Sex	0.55	0.57	0.53	0.54	0.56
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Price [a]	3596.78	9139.81	4249.80	5845.07	1420.73
	(9075.77)	(15763.70)	(9465.02)	(10723.67)	(5414.51)
Travel Time	2.29	6.65	2.69	5.14	0.22
	(5.46)	(9.06)	(5.07)	(7.41)	(2.29)
Tontine [a]	1810.62	1206.73	1128.06	3419.78	1754.97
	(13106.16)	(3572.66)	(2743.82)	(25750.63)	(10939.53)
Ouidah	0.43	0.77	0.36	0.68	0.35
	(0.50)	(0.43)	(0.48)	(0.47)	(0.48)
Peasant	0.39	0.31	0.34	0.48	0.41
	(0.49)	(0.47)	(0.47)	(0.50)	(0.49)
Fever	0.47	0.27	0.49	0.45	0.50
	(0.50)	(0.45)	(0.50)	(0.50)	(0.50)
Respiratory infections	0.12	0.06	0.11	0.11	0.14
	(0.32)	(0.24)	(0.31)	(0.31)	(0.34)
Parasitic disease	0.06	0.10	0.06	0.02	0.07
	(0.24)	(0.30)	(0.24)	(0.15)	(0.25)
Schooling	0.27	0.46	0.24	0.32	0.24
	(0.44)	(0.50)	(0.43)	(0.47)	(0.43)
# Active	5.46	6.50	5.94	6.08	4.72
	(3.59)	(4.21)	(3.85)	(3.51)	(3.19)

[a] In CFA Francs.

are left in our sample. In the data, individuals report either self-medication, or to have sought care at either of traditional healers, hospital, communal health centers or private clinics. The data also contain numerous information on socio-economic variables at the household/individual level.

Table 1 presents descriptive statistics of the sample. For the purpose of the paper, self-medication and traditional healers have been merged into the single category, "self-treatment" [8]. As can be seen, self-treatment is by far the most frequent form of treatment. The category "hospital or CSSP" includes those visits that were made at either the hospital in Cotonou or the hospital in Ouidah (CSSP). Both these hospitals are accessible to individuals living in the District of Ouidah. Private clinics are owned and operated by doctors, many of whom also work at one of these hospitals.

[8] This is a fairly common practice (see Mwabu et al., 1993). In our sample only 29 individuals reported seeking care at traditional healers.

The average age of ill individuals is 28.4. It appear the young are more inclined to seek care at the CHC and private clinics and that older individuals are more likely to turn to self-treatment or to seek care at the hospital. The proportion of women/men is relatively the same at all providers. The price variable shows considerable variation across providers. Self-treatment has the lowest average price. The price essentially represents the expenditures made for buying medicine at the pharmacy or at the traditional healer. In the middle range, we find the average price at the CHC and private clinics. Finally, the average price at the hospital is by far the highest. This may reflect either that people who are treated there have more serious illnesses or receive better quality care.

The time required to receive care includes travel time back and forth and waiting time. In the case of self-treatment it includes the time it took individuals to buy the medicine. The CHC has the lowest average travel time next to self-treatment. This is not surprising since they are strategically located to be relatively accessible to all villagers. Most private clinics are located in the so-called Urban Community of Ouidah (UCO), which comprises the four most populated villages that make up the town of Ouidah. Finally, the travel time to the hospital, not surprisingly, is highest.

The variable tontine represents the monthly average saving of the head of the household. The large standard error is due to the fact that only 29.8% of the sample participates in this activity. Again, no clear pattern emerges, except perhaps that individuals seeking care at private clinics tend to have higher average tontine. The standard error on this variable is so large that it precludes any significant statistical inference. The same remarks apply to monthly income, where again no clear pattern emerges.

Recall that there are nine communes in the District of Ouidah. The dummy variable Ouidah is equal to one if an individual resides in the UCO. The table shows that 43% of the sample resides in the UCO. Yet, they are responsible for 77% of the consultations made at the hospital. Similarly, 68% of the consultations made at private clinics were from individuals residing in the UCO.

The variable peasant is a dummy variable that represents whether the household owns or rents agricultural land. Overall, 40% of the households are involved in agricultural activities of some kind. The next three lines of Table 1 are dummy variables representing the most frequent diagnostics reported by individuals.Recall that the interviews were conducted by doctors and/or medical staff from the CHC in Pahou. To avoid misreporting from individuals who self-treated, it was decided to report diagnostics rather than disease. In this case, the distribution across providers shows a clear break between hospital on one hand and other providers on the other hand. Indeed, roughly 50% of the visits made at the CHC, private clinics or self-treatment concern fever, whereas it only represents 27% at the hospital. Similarly, visits made at the hospital for respiratory infections represent half those made at the other three providers.

The variable schooling is a dummy variable representing whether an individual older then 15 years of age has more than primary schooling. Interestingly, it appears that those who visited the hospital have more schooling on average. This may in fact be because individuals living in the UCO have more schooling on average. Indeed, for those living in the UCO the mean value is 0.36, whereas it is only 0.18 for those living outside the UCO. Finally, the last line of Table 1 reports the average number of non-schoolers per household that are involved in paid work.

5. Empirical results

In order to estimate the model, data is needed on the relative prices individuals face at the different providers and the travel time to each. Naturally, we only observe the price and the travel time to the chosen provider. We follow most studies and estimate hedonic price and travel-time equations based on the sub-samples of individuals seeking care at each different provider (see e.g., Gertler et al., 1987. This procedure raises selectivity problems that must be accounted for since the travel-time and price faced by an individual choosing a given alternative are likely not representative of those faced by the "average" individual. The details of these estimations are not presented for the sake of brevity, but are available upon request.In the travel time equations we account for the type of vehicle owned by each household. Thus we implicitly account for monetary cost associated with travel.

The income variable is defined as annual family income converted on a monthly basis. It includes paid activities of each member of the household as well as income accruing from the sale of farm and fishing products over the year. This definition was preferred over income earned during the two weeks prior to the survey for several reasons. First, income exhibits strong seasonal fluctuations in the data. Recall that the survey was conducted between the months of May and September 1992. Hence, some households were interviewed at the peak of the harvest season while others were interviewed between harvest seasons [9]. Secondly, a certain number of individuals are civil servants. These individuals are typically paid at the beginning of each month. When interviewed in the middle of a month, many individuals report having no or very little income. Thirdly, annual family income is a good approximation to the household permanent income. Finally, Gertler et al., 1987 report evidence that the appropriate budgeting horizon for rural households is approximately a month.

[9] There are essentially two harvest seasons in the District of Ouidah. The first harvest occurs around the end of June and the next occurs toward the end of August. Some households sell parts of their crops immediately and others wait until the end of November to benefit from higher prices.

Table 2
Censored regression — tontine tontine/1000, Income/1000

Variable	Coefficient	*T*-ratio	Mean of *X*
A: Individual Characteristics			
Constant	−11.346	−2.207	1.000
Sex-head	−3.116	−0.940	0.366
Age-head	−0.183	−2.215	44.793
# Wifes	−9.507	−4.447	0.735
# Children	−1.313	−2.872	4.255
# Dependents	3.614	9.236	4.043
Peasant	7.190	2.897	0.394
Cattle	0.639	2.000	0.300
Income	0.311	5.931	10.755
B: Environmental variables			
Comm-2	−4.873	−1.103	0.126
Comm-3	0.386	0.085	0.087
Comm-4	5.025	1.328	0.168
Comm-5	2.321	0.583	0.141
Comm-6	−4.121	−0.680	0.056
Comm-7	−3.093	−0.703	0.126
Comm-8	12.772	2.192	0.026
Comm-9	0.243	0.059	0.136
Well	−3.921	−1.794	0.380
σ	0.125	20.245	
Observations		2432	
Log-likelihood		−3306.7	

Notes: The regression also includes a set of dummy variables for feedstock, type of house and access to running water.
Among the 432 married men, 311 had 1 wife, 95 had 2, 21 had 3, 4 had 4 and 1 had 5.

Following our discussion of the theoretical model, the tontine must be considered endogenous to the choice of provider. This variable must thus be instrumented to allow consistent estimation of the discrete choice model. An additional difficulty arises due to the fact that this variable is censored at zero. It is best then to estimate a tontine function based on a censored regression model (tobit) in a first step and to estimate the provider choice model conditional on the predicted values in the second step. Note also that the estimation is performed using the whole sample since the decision to participate in a tontine must be made before the disease occurs.

Table 2 presents the results of fitting a set of exogenous covariates to the tontine data. The first panel concerns the characteristics of the household (vector A) whereas the second panel concerns environmental variables (vector B). As shown in the top panel, the tontine is negatively and significantly related to age of head, number of wives and number of children, and positively related to number of dependents [10]. Households that cultivate land (peasant) as well as those who raise cattle tend to save more than households not involved in these activities. Finally, income has a positive and significant impact on tontine. In the bottom panel, most community dummy variables are not statistically significant. On the other hand, having access to running water or to a private well (well) significantly reduces saving. In terms of our theoretical model, this variable indicates that, ceteris paribus, individuals who have access to a good hygienic environment have a lower probability of bad state of nature and hence will tend to save less. Although this is the only available variable to control for the quality of an individual's environment, it probably captures its essential features. On the basis of these parameter values, we predict for each household a level of tontine that is used in the provider choice model.

5.1. Parameter estimates

Table 3 presents the parameter estimates of the three specifications, namely the MP, IMP and ML. The first part of the table concerns provider-specific variables, i.e. prices and travel time. The second panel concerns the individual-specific attributes. Finally, the third panel presents the estimated correlation matrix of the probit model. Note that since the MP specification nests the IMP, the independence of the error terms can easily be tested on the basis of a likelihood ratio test. Indeed, $-2(\log L^{\mathrm{IMP}} - \log L^{\mathrm{MP}}) \sim \chi^2(5) = 18.48$ [11]. Furthermore, the first element of the decomposition must be normalized to unity to allow identification of the remaining parameters. Therefore the assumed independence between the error terms implicit in the IMP must be rejected ($\chi^2_{0.95}(5) = 11.07$, $\chi^2_{0.99}(5) = 15.08$). It remains to see if imposing independence has strong consequences on the estimated own and cross-price elasticities.

Overall, the qualitative results of all three specifications are similar: The statistically significant parameter estimates are essentially the same across specification. The price has a negative and significant impact on the choice of a given alternative and is of the same magnitude in the PM and IMP. Surprisingly, travel time has a positive impact, but is only statistically significant in the probit specification. This result can arise for at least two reasons. First, it can be that when the severity of an illness increases, individuals tend to seek care at the hospital or at private clinics, which are more distant than other providers on average. Hence, severity and distance could be correlated. Since we do not control for the severity of the illness, the distance variable may in fact proxy the severity.

[10] The number of dependents includes individuals living in the same house, other than the head's children. These usually are members of the extended family, i.e. either spouses' brothers, sisters, parents, etc.

[11] There are only five degrees of freedom since in practice we estimate the Cholesky decomposition of Σ, rather than Σ itself, which contains six parameters.

Table 3
Parameter estimates

	Probit Model			Independent Probit Model			Logit Model		
	Hospital	CHC	Private	Hospital	CHC	Private	Hospital	CHC	Private
lnPrice		−0.297 [a]			−0.355 [a]			−0.616 [a]	
		(0.097)			(0.171)			(0.244)	
lnTime		0.345 [a]			(0.110)			0.623	
		(0.130)			(0.081)			(0.407)	
Intercep	−2.060 [a]	−0.369	0.023	−3.070 [a]	−0.544	0.442	−4.360 [a]	−0.551	0.295
	(0.817)	(0.571)	(0.520)	(1.320)	(0.750)	(0.897)	(1.760)	(0.910)	(1.220)
Income	0.130 [b]	0.006	−0.048	0.183	0.017	−0.129	0.269 [b]	0.000	−0.181
	(0.077)	(0.057)	(0.053)	(0.120)	(0.074)	(0.093)	(0.153)	(0.090)	(0.118)
Tontine	−0.032 [b]	−0.006	−0.006	−0.055 [b]	−0.015	0.011	−0.078 [a]	−0.014	0.005
	(0.020)	(0.011)	(0.010)	(0.035)	(0.020)	(0.025)	(0.039)	(0.019)	(0.024)
Age	−0.036	−0.023	−0.066	−0.050	−0.036	−0.128	−0.049	0.023	−0.173
	(0.071)	(0.055)	(0.045)	(0.0998)	(0.071)	(0.080)	(0.141)	(0.100)	(09.109)
Comm-2	−0.136	0.724 [a]	1.280 [a]	−0.798	0.966 [a]	2.090 [a]	−0.540	1.120 [a]	2.980 [a]
	(0.350)	(0.250)	(0.256)	(0.736)	(0.302)	(0.354)	(0.727)	(0.474)	(0.505)
Comm-4	−0.096	−0.783 [a]	0.122	−0.225	−0.893 [a]	0.229	−0.324	−1.310 [a]	0.553
	(0.212)	(0.219)	(0.187)	(0.382)	(0.241)	(0.285)	(0.480)	(0.331)	(0.389)
Comm-5	−1.260 [a]	0.128	0.070	−2.220 [a]	0.223	0.029	−2.740 [a]	0.173	−0.092
	(0.468)	(0.172)	(0.185)	(0.942)	(0.217)	(0.385)	(1.110)	(0.279)	(0.513)
Comm-7	−0.529	−0.065	−0.302	−0.538	0.052	−0.991 [a]	−0.814	0.082	−1.500 [b]
	(0.400)	(0.216)	(0.229)	(0.608)	(0.258)	(0.516)	(0.892)	(0.328)	(0.852)
Comm-9	−0.808 [a]	−0.189	−0.395 [b]	−1.190 [a]	−0.068	−0.781 [b]	−1.200 [a]	−0.180	−1.510 [a]
	(0.324)	(0.209)	(0.219)	(0.570)	(0.254)	(0.436)	(0.612)	(0.337)	(0.703)
Fever	−0.741 [a]	−0.189	−0.337 [a]	−0.948 [a]	−0.262	−0.460 [a]	−1.390 [a]	−0.342	−0.697 [a]
	(0.196)	(0.135)	(0.121)	(0.304)	(0.173)	(0.220)	(0.401)	(0.215)	(0.289)
Resp. Inf.	−0.838 [a]	−0.321	−0.481 [a]	−1.250 [a]	−0.412 [b]	−0.725 [a]	−1.960 [a]	−0.443	−0.940 [a]
	(0.362)	(0.204)	(0.173)	(0.452)	(0.251)	(0.324)	(0.697)	(0.318)	(0.410)
Para. Dis.	−0.357	−0.375	−0.766 [a]	−0.469	−0.373	−1.390 [a]	−0.579	−0.551	−2.030 [a]
	(0.379)	(0.271)	(0.302)	(0.532)	(0.309)	(0.512)	(0.615)	(0.399)	(0.712)
Acute Ill.	0.050 [a]	0.037 [a]	0.038 [a]	0.087 [a]	0.062 [a]	0.057 [a]	0.122 [a]	0.070 [a]	0.072 [a]
	(0.024)	(0.016)	(0.016)	(0.039)	(0.018)	(0.023)	(0.048)	(0.023)	(0.030)
School	0.326 [b]	−0.024	0.109	0.512 [b]	0.019	0.180	0.792 [a]	−0.007	0.238
	(0.174)	(0.136)	(0.116)	(0.273)	(0.181)	(0.210)	(0.364)	(0.224)	(0.284)
# Active	0.071 [a]	0.050 [a]	0.046 [a]	0.099 [a]	0.066 [a]	0.059 [a]	0.142 [a]	0.082 [a]	0.078 [a]
	(0.022)	(0.020)	(0.016)	(0.035)	(0.021)	(0.025)	(0.041)	(0.027)	(0.034)
	Correlation Matrix								
	Hospital	CHC	Private						
Hospital	1.000	0.154	0.658 [a]						
	(−)	(0.334)	(0.275)						
CHC		1.000	0.845 [a]						
		(−)	(0.444)						
Private			(−)						
log-likelihood		−811.55			−820.79			−821.45	

[a] Significant at 5%.
[b] Significant at 10%.

Second, we have no information on the hourly wage rate in our data. Hence, individuals with a low opportunity cost of time may be willing to travel to more distant providers when the severity of the illness increases [12].

The (predicted) tontine has a negative and statistically significant impact on hospital in all specifications. Hence, it seems individuals who participate in a tontine systematically favor self-medication or traditional healers over hospital. The level of tontine does not have any effect on other providers. This result may indicate that people who intend to self-treat or to consult a traditional healer must save because they probably have to pay cash for the medicine and/or the services. On the other hand, deferred payment may be available at the hospital, in which case precautionary saving is less important.

The income variable has a positive and statistically significant impact on hospital in the MP and ML specifications. It would thus appear treatment at the hospital is a normal good. Several Commune dummies have been incorporated into the regression to capture unobserved quality of care across communes. Note that the communes 1, 3, 6 and 8 do not appear in the table. This is because some providers were visited by as little as 2 or 3 individuals in some of the communes, resulting in collinearity problems. Hence, for comparison purposes, the omitted category remains commune 1, which is the most populated and which hosts the hospital and a few private clinics. Note first that all specifications imply that there are no differences between neighboring communes 1, 2 and 4 as regards visits to the hospital. Yet, there are significant differences concerning visits to the CHC and to private clinics. Since we are controlling for travel time and prices, these dummy variables are presumably capturing differential quality at other providers. In communes 5 and 9, they all imply that the probability of visiting the hospital is lower than in commune 1, but it does not seem to be the case in commune 7.

The next three rows show the impact of the main diagnostics on the choice of provider. Overall, they nevertheless imply that when suffering from a disease associated with one of these diagnostics, individuals tend to turn towards self-treatment and traditional healers. Not surprisingly, the next line indicates that when suffering from an acute illness, individuals favor the hospital, the CHCs or private clinics over self-medication [13]. Next, having more than primary education increases the probability of seeking care at the hospital. This is consistent with the claim that better educated individuals are more inclined to use modern medicine because they can better use it. This result is also consistent with those found by Gertler et al., 1987, Mwabu et al., 1993.

Finally, the more there are active members in a household, the more likely individuals will turn away from self-medication. One can conjecture that by

[12] Some studies that lacked data on hourly wage rate and severity of illness have nevertheless found a negative sign for distance, see Gertler et al., 1987, Mwabu et al., 1993.

[13] Acute illness is defined as either a wound, an injury or a bruise requiring immediate treatment.

pooling resources, bigger households can offer some form of insurance to its members and afford better care.

The last panel of Table 3 presents the correlation matrix of the probit specification. Recall that this matrix is the correlation of the difference between the error terms of each alternative and self-treatment. It indicates the degree of association between the differentiated error terms. It thus appears the unobserved characteristics of the hospital are strongly correlated to those of the private clinics and similarly for the private clinics and the CHCs.

5.2. Elasticities and policy simulations

Table 4 presents the own and cross price elasticities [14]. The elements on the diagonal are the own-price elasticities and those off-diagonal represent the cross-price elasticities. The figures in parentheses represent the asymptotic standard errors of the elasticities [15]. Nearly all the elasticities are statistically significant at 5% or better. This is not surprising given the large number of parameter estimates that are statistically significant. Notice first that the own-price elasticities associated with hospital and private clinics are unusually high. This is essentially due to the fact that only 6.5% and 17.5% of total visits were made at these providers, respectively. In general, the three specifications predict own-price elasticities of the same magnitude. The main differences concern cross-price elasticities. In the logit specification, as mentioned earlier, all the cross-price elasticities are constrained to be equal. For example, a one percent increase in hospital fees will have the same impact (0.356) on all other providers. In the probit specification, the same fee hike will have a significant impact on private clinics and to a lesser extent on self-treatment. It will have virtually no impact on CHCs. The cross-price elasticities implied by the IMP are quite close to those of the ML, although they are not constrained to be constant. If the authorities decide to increase prices at the various CHCs, the MP predicts the decrease in total visits will be compensated by a commensurate increase at the private clinics and in a small increase in self-treatment. In the logit specification this fee hike will translate into an even impact on each provider, whereas the IMP predicts the increase will be more concentrated on hospital and private clinics. The same response arises when increasing fees at private clinics or for self-treatment. The overall result is that the

[14] The elasticities of the ML are computed from relatively simple expressions. Unfortunately, the elasticities of the IMP and MP specifications don't have a closed form solution. We thus calculate the elasticities by increasing the price of each alternative by a small proportion (0.00001) and divide the relative change in the probabilities by the same proportion. In the table, we report the mean over all individuals. Note that the mean elasticities are very robust to the proportional change used. We experimented with values ranging between 0.01 and 0.0000001 and always obtained virtually the same results.

[15] The standard errors of the elasticities of all three specifications do not have a closed form solution. For the ML specification we follow Horowitz, 1979 and use a first-order linear approximation of the true variance of the probabilities. For the IMP and MP specifications we calculate the standard errors using the so-called "delta method", which is very similar to the method proposed by Horowitz, 1979.

Table 4
Own and cross-price elasticities of demand

	Elasticity of demand (asymptotic standard errors in parentheses)			
	Hospital	CHC	Private clinic	Self-treatment
	Probit model			
Hospital	−4.169 [a]	0.021 [b]	0.688	0.241 [a]
	(1.869)	(0.012)	(0.590)	(0.077)
CHC	0.116 [a]	−2.477 [a]	2.262 [a]	0.732 [a]
	(0.044)	(1.177)	(0.915)	(0.245)
Private clinic	2.183 [a]	1.462	−4.269 [a]	0.577 [a]
	(0.923)	(0.960)	(1.114)	(0.176)
Self-treatment	1.139 [b]	0.771 [a]	1.005 [a]	−1.161 [a]
	(0.658)	(0.328)	(0.293)	(0.353)
	Independent probit model			
Hospital	−5.658 [a]	0.332 [a]	0.399 [a]	0.315 [a]
	(2.631)	(0.154)	(0.180)	(0.143)
CHC	1.619 [a]	−2.371 [a]	1.363 [a]	1.051 [a]
	(0.753)	(1.069)	(0.648)	(0.499)
Private Clinic	1.029 [a]	0.687 [a]	−3.654 [a]	0.685 [a]
	(0.459)	(0.313)	(1.642)	(0.302)
Self-Treatment	1.477 [a]	1.067 [a]	1.305 [a]	−1.527 [a]
	(0.686)	(0.494)	(0.583)	(0.678)
	Logit model			
Hospital	−4.966 [a]	0.356 [a]	0.356 [a]	0.356 [a]
	(2.088)	(0.149)	(0.149)	(0.149)
CHC	1.459 [a]	−3.161 [a]	1.459 [a]	1.459 [a]
	(0.638)	(1.324)	(0.638)	(0.638)
Private clinic	0.857 [a]	0.857 [a]	−3.956 [a]	0.857 [a]
	(0.360)	(0.360)	(1.663)	(0.360)
Self-treatment	1.536 [a]	1.536 [a]	1.536 [a]	−2.007 [a]
	(0.650)	(0.650)	(0.650)	(0.842)

[a] Significant at 5% or better.
[b] Significant at 10%.

MP is better able to uncover which providers are substitutes. The ML, by construction, does not allow this. The IMP, although a restrictive estimator, allows richer responses than the ML but, evidently, not as much as the MP.

To gain further insight into the behavior of ill individuals, Table 5 reports the simulation results of increasing various exogenous variables by as much as 10%. Inspection of the table reveals pretty much the same pattern as that observed in Table 4; the simulation from the ML and IMP models are quite similar but those from the MP model differ substantially. In particular, raising the prices at the hospital by 10% decreases nearly by half the expected number of visits. Increasing the fees by 10% at the private clinics also lowers nearly by half the expected number of visits. In the former case, the decrease is compensated almost completely by increases at private clinics. In the latter case, the increase is divided

Table 5
Policy simulations

	Probability of selecting			
	Hospital	CHC	Private clinic	Self-treatment
Sample proportion	0.065	0.318	0.175	0.442
	Probit model			
10% Increase in hospital fees	0.037	0.316	0.193	0.455
Relative change	(−0.431)	(−0.006)	(0.103)	(0.029)
10% Increase in CHC fees	0.064	0.235	0.226	0.475
Relative change	(−0.015)	(−0.261)	(0.291)	(0.075)
10% Increase in clinic fees	0.080	0.360	0.090	0.470
Relative change	(0.231)	(0.132)	(0.486)	(0.003)
10% Increase in income	0.083	0.326	0.149	0.442
Relative change	(0.277)	(0.025)	(−0.149)	(0.000)
10% Increase in tontine	0.063	0.315	0.177	0.445
Relative change	(−0.031)	(−0.009)	(0.011)	(0.007)
	Independent probit model			
10% Increase in hospital fees	0.043	0.326	0.180	0.452
Relative change	(−0.338)	(0.025)	(0.029)	(0.023)
10% Increase in CHC fees	0.073	0.252	0.193	0.482
Relative change	(0.123)	(−0.208)	(0.103)	(0.090)
10% Increase in clinic fees	0.071	0.336	0.132	0.461
Relative change	(0.092)	(0.057)	(−0.246)	(0.043)
10% Increase in income	0.082	0.324	0.152	0.442
Relative change	(0.262)	(0.019)	(−0.131)	(0.000)
10% Increase in tontine	0.065	0.317	0.175	0.443
Relative change	(0.000)	(−0.03)	(0.000)	(0.002)
	Logit model			
10% Increase in hospital fees	0.041	0.326	0.180	0.453
Relative change	(−0.369)	(0.025)	(0.029)	(0.025)
10% Increase in CHC fees	0.074	0.231	0.1998	0.497
Relative change	(0.138)	(−0.274)	(0.131)	(0.124)
10% Increase in clinic fees	0.071	0.341	0.123	0.465
Relative change	(0.092)	(0.072)	(−0.297)	(0.052)
10% Increase in income	0.081	0.321	0.154	0.443
Relative change	(0.246)	(0.009)	(−0.120)	(−0.002)
10% Increase in tontine	0.064	0.317	0.175	0.443
Relative change	(−0.015)	(−0.003)	(0.000)	(0.002)

between hospitals and CHCs. Neither the ML nor the IMP are able to uncover such substitution. Finally, a 10% increase in CHC fees translate into a 26% fall in visits and a 29.9% increase in visits at private clinics. Again, neither the ML nor the IMP capture this substitution. The predictions concerning increases in income and tontine, on the other hand, are very similar for the three specifications. In particular, they all predict that a 10% increase in tontine has almost no impact on provider choice.

6. Conclusion

Many countries in Africa are currently considering decentralizing their health care systems, much in line with the so-called Alma Ata resolutions (see e.g Wouters, 1991). In Bénin, it was decided to experiment full decentralization in the District of Ouidah and to study its consequences before extending it further. An in-depth survey was thus conducted during the summer of 1992.

As of now, the experiment conducted in the District of Ouidah does not allow full cost recovery. Authorities will eventually have to raise prices at the hospitals and/or at the CHCs. Many are concerned raising fees will drive ill individuals toward more traditional health providers or self-care. The motivation behind this paper was to establish whether such fears are grounded. A careful reading of the empirical literature on primary health care demand reveals that nearly all analyses are conducted using the multinominal logit specification (ML). Given the severe constraints imposed by that particular specification, we decided to utilize a more general framework, the multinominal probit (MP) and the independent multinominal probit (IMP) specifications and compare the resulting elasticities of demand. The use of the MP model has been hampered in the past by the considerable computing costs it involves. Recent advances have nevertheless made it relatively affordable. The absence of studies using the IMP specification is surprising since it does not involve much more computing time than the ML and yet allows somewhat richer responses.

It appears the elasticities of demand are sensitive to the statistical model one uses. For instance, when we increase fees at a given provider, the MP shows there is substantial substitution between two providers at most. The IMP tends to spread the response more or less evenly across providers and the ML, on the other hand, imposes a proportional change for every provider. There are little reasons to believe a priori this should be the case. Consequently, it may be inappropriate to formulate policy recommendations based on the ML model, which is by far the most widely used estimator in the literature. Furthermore, the statistical independence implied by the IMP has been rejected by the MP specification. There are thus little reasons to believe the independence implied by the ML has any justification.

A second concern in this paper arose from the fact that most illnesses found in rural areas of Bénin are endemic. Indeed, most individuals will eventually suffer from one of many parasitic diseases. To the extent these are predictable events, individuals should save a fraction of their income for precautionary purposes. If fact, we do observe as many as 30% of the households participating in a rotating credit system (tontine). On the other hand, little is know about the possibilities to defer payments for health care at various providers. Surely, this provider-specific characteristic may be just as important as relative prices and travel time. We thus studied the impact saving may have on the choice of a particular provider in a rather cavalier fashion. Our results show weak evidence that individuals who save part of their earnings tend to favor self-treatment or traditional healers. Given the potential importance of this aspect of health care demand, future work should try to measure the consequences varying modes of payments may have on provider choice.

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