An Empirical Model of Primary Health Care Demand in Bénin

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Abstract

The purpose of this paper is to provide empirical evidence on the sensitivity of primary health care demand with respect to price and travelling time in rural Bénin. The data we use come from an experiment being conducted in the area of Pahou-Avlékété. The theoretical model follows closely that of Heller (1982). The estimation strategy relies for the most part on count data models. Variants of the basic Poisson model are called upon to test overdispersion in the data. The robustness of the parameters is investigated by computing pseudo and quasi-generalized pseudo maximum likelihood estimators. Our results indicate that non-price rationing (travelling time) has a large impact on demand and that the wealthier individuals are less sensitive. Furthermore, the demand appears to be relatively inelastic with respect to price.

1 Introduction

It is usually acknowledged that a high level of literacy and generalized good health are sine qua non conditions to durable development. The interest for the study of health care demand by economists has its roots in this simple but fundamental reality.

Much of the empirical research in economics has thus been concerned with studying the impact of price and travel time on the demand for health care. The recent empirical literature has given rise to two conflicting sets of results. On one hand, some studies find little sensitivity of the demand for health care with respect to price and travel time [Akin, Griffin, Guilkey and Popkin(1984, 1986), Heller (1982)] while on the other hand, some studies conclude the opposite [Dor, Gertler and van der Gaag (1987), Gertler, Locay and Sanderson (1987), Gertler and van der Gaag (1990), Mwabu (1986), Mwabu, Ainsworth and Nyamete (1993)].

The purpose of this paper is to provide further empirical evidence on the sensitivity of the demand for primary health care (PHC). To this end, we use a newly created data set stemming from an experiment on primary health care that is being conducted in the Pahou-Avlékété region of the République du Bénin. This experiment received significant recognition in 1991 by being awarded the Sasakawa prize for its novel approach in procuring PHC.

Contrary to most recent papers on the demand for primary health care in developing countries, we do not model provider choice. Instead, as in Heller (1982), we study another dimension of the demand, namely the frequency of visits to health care facilities. The motivation for focusing on this dimension of demand will be better understood when we elaborate on the institutional environment of the experiment.

The theoretical model follows closely that of Heller (1982). The essence of the model rests on the (realistic) assumption that each spell of illness requires a minimum number of visits to a health centre. Anything above this is influenced by economic conditions; income, relative prices of alternatives, opportunity cost of time, etc. Our estimation strategy relies for the most part on count data models. Variants of the basic Poisson model are called upon to test various statistical assumptions, namely that of overdispersion in the data. The robustness of the Poisson estimates is investigated by comparing them with pseudo and quasi-generalized pseudo maximum likelihood estimates as suggested by Gourieroux, Monfort and Trognon (1984b). We also estimate a hurdle version of the Poisson model that was suggested by Mullahy (1986). This model allows decomposing the data generating process into a binomial probability model that governs the binary outcome of whether a count has a zero or positive realization, and into a conditional distribution for the positives.

Although data limitations constrain us to work with reduced form models, most parameters have the expected (structural) sign, and most are statistically significant. In essence, our results indicate that non-price rationing plays an important role in reducing health care demand in rural Bénin and that the demand is relatively inelastic with respect to price. Furthermore, the time-price elasticity of the demand is a decreasing function of income, a result that was found recently by Gertler et al. (1987) and Mwabu et al. (1993) and which has significant policy implications.

The paper is organized as follows. Section 2 presents the institutional environment in which the experiment is being conducted. Section 3 presents the theoretical model. Section 4 discusses empirical issues and describes different estimators. Section 5 presents the results and Section 6 concludes.

2 Data and Institutional Environment

The République du Bénin is a small mainly rural country located in the Golf 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, traumas 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 nation-wide programs, it was decided to experiment certain strategies on a small scale and to proceed to periodic evaluations.

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. The Communes are subdivided into three regions (henceforth A, B, C) that each represent a landscape likely to be encountered in the rural country. Region A comprises 4 villages and is characterized by flat terrain. In one of the villages (Pahou), a Communal Health Centre (known as the CREDESA - Centre Régional pour le Développement et la Santé) has been erected to provide health care to the individuals of the three regions. Hence, individuals in Region A have the easiest access to the health centre. On average, they are located only 2.6 km away. Region B comprises 9 villages located on a plateau approximately 5 km from the communal health centre (CHC). Finally, Region C comprises 6 villages located in and around marshlands. The main mean of transportation is the pirogue. These villages are not only the farthest from the CHC (6.6 km on average), but have poorest access. During the rain seasons, direct road access is impossible. Instead a 25 km detour must be made.

Since its erection in 1983, the main health strategy at the CHC has been based on a referral system. Essentially, individuals in the different villages must consult a Village Health Agent (VHA) for all diseases. These VHA are laymen that were trained by the CHC doctors to diagnose basic diseases using a 'diagnostic tree'. If the illness is simple to treat, the VHA can provide the necessary medication. If the illness is too severe or can not be diagnosed, they are referred to the CHC. Any individual who consults the CHC without being referred by a VHA will pay twice and in some cases three times the usual fee for the treatment. Needless to say, the administrative files contain very few such cases.

The data we use in this study come from three different sources. First, before the activities of the centre started, an exhaustive census covering the three regions was conducted in may 1983. The census was periodically up-dated to account for migration, death, birth, etc. Each household was associated with its own identifier, and each individual within the household was similarly identified with his own identifier. According to the demographic up-date of 1987, the population of Pahou-Avlékété was 18,441. The file contains information on the age, sex, migration status and relation to head. Another survey was conducted in 1986 to gather information on socio-economic variables; means of transportation, occupations, house ownership, house characteristics, participation in a tontine, etc. Finally, we have access to the administrative file of the health centre. Each time an individual shows up to receive medical care, the diagnostic and the cost is recorded on the basis of his household/individual identifier. Thus, the information can be linked to the census and socio-economic files. Over the period 1983-1987, 17,214 visits were made to the CHC by 6,973 different individuals.

Table 1 presents some characteristics of our sample. As can be seen, the three regions have approximately the same population size, and women represent a larger proportion of the population. The population is very young in all three regions due to high fertility rates. Also, the villages of Region C are on average slightly more distant to the health centre than those of Region B. The distribution of occupations shows there are significant differences between regions. In reading the data, one must remember that individuals usually engage in more than one occupation. Hence the means of the different occupational dummies do not add to one. Region A is the more 'urbanized' of the three. Sale of own produce and fishing is lowest and salaried work is highest. Region B lies somewhere in the middle. Finally, fishing is most important in Region C and salaried work is lowest. The distribution of means of transportation also differs significantly across regions. For example, car, motorcycle and moped ownership is by far higher in Region A than in B and C. Overall, the main means of transportation is still the bicycle.

The file on health care contains information on 26 different diagnostics ranging from fever and allergies to hypertension. Yet three diagnostics account for as much as 60% of the total visits to the health centre. Table 2 shows the distribution of diagnostics across the three regions. By far the most frequent one is fever, followed by respiratory infections and parasitic diseases. The distributions are pretty similar in Region A and Region B, but differ slightly in Region C, where respiratory infections are more prevalent presumably because of the extremely humid climate. For reasons to be explained later we will limit our analysis to these three diagnostics.

One serious limitation of the data is that it contains no information on individual income or hours worked. We must thus rely on instruments to approximate household permanent income and wage rate. Another limitation is that the information on socio-economic variables was gathered in 1986 and was never up-dated. To the extent there is practically no growth in this small rural area, it may be reasonable to assume there was no capital accumulation or depreciation. In other words, we must assume there was no change in households' wealth throughout the period of analysis.

Our aim in this paper is to study the sensitivity of the demand for primary health care to various economic factors. In what follows, we describe the theoretical model that will be used in interpreting the econometric results.

3 The Theoretical Model

In general, an individual's health status is determined by behavioral, physiological and environmental factors. For example, the virulence and prevalence of pathenogenic agents in a certain area determine the risk of illness. Greater consumption of clothing, shelter, treated water and the like increases the ability to resist infection. Finally, habits and hygiene may affect the overall health status. We thus follow Heller (1982) and assume that the health status is produced according to the function:

$$H = H(C; A, E, d), \tag{1}$$

where C is a composite commodity of goods and services, A is the age of the individual, E measures the hygienic quality of the environment, and d is a measure of the virulence of the disease agents in the community. From the above discussion, $H_c \geq 0$. Age is introduced in the function because an individual's ability to insulate against disease decreases with age. In developing countries, one might suspect a U-shaped relation between age and morbidity; new borns and infants are vulnerable to many diseases. During adulthood, bodily aging is akin to depreciation of human capital.

We assume that each spell of illness requires minimal medical care, m, which is related to consumption in the following way:

$$m = m(H) = m(C; A, E, d), \tag{2}$$

with $m_c < 0$ and $m_{cc} > 0$. In other words, the healthier the individual, the less he needs to consume medical care for a given episode of illness. Thus, m is the minimal level of medical care conditional on the occurrence of a spell of illness. Consumption of medical care can be greater than m. Indeed, two individuals faced with the same illness may consume different amounts of medical care depending on preferences, income and other economic variables. Consumption in excess of m, $\tilde{m}$, may take the form of more frequent visits to the doctor or better quality care (hospital vs clinic). As stressed by Heller (1982), the main difficulty is that we empirically only observe $M = m + \tilde{m}$.

The individual is assumed to derive utility only from C and $\tilde{m}$:

$$U = U(C, \tilde{m}), \tag{3}$$

where $U_c, U_{\tilde{m}} > 0$ and $U_{cc}, U_{\tilde{m}\tilde{m}} < 0$. Note we implicitly assume no utility is derived from the consumption of m. The utility index is maximised subject to a budget constraint. Let $\mu = y + \omega T$ be the 'full income', where y is non-labour income, ω is the hourly wage rate and T is the time endowment. In the communities we are studying, the households produce the majority of the commodities they consume. Following Acton (1975), we thus assume that both C and $\tilde{m}$ command a cash price and a time price. More precisely, we write the budget constraint as:

$$\mu = y + \omega T = (P_c + \omega\nu)C + (P_m + \omega\psi)(m + \tilde{m}), \tag{4}$$

where ν is the time necessary to produce C, and ψ is the time spent obtaining medical care. Maximization of (3) with respect to (4) gives rise to the following Lagrangean programme:

$$\phi = U(C, \tilde{m}) + \lambda[y + \omega T - (P_c + \omega\nu)C - (P_m + \omega\psi)(m(C) + \tilde{m})]. \tag{5}$$

The first order condition is

$$\frac{U_c}{(P_c + \omega\nu) + (P_m + \omega\psi)(m'(C))} = \lambda = \frac{U_{\tilde{m}}}{(P_m + \omega\psi)}. \tag{6}$$

Since $m'(C) < 0$, $(P_c + \omega\nu) + (P_m + \omega\psi)m'(C) < (P_c + \omega\nu)$ and hence, the demand for the composite commodity is greater than if $m'(C) = 0$. In other words, the price of the composite commodity is $(P_c + \omega\nu)$ less the induced savings of necessary medical care. Using second order conditions it can be shown that the own-price effects on C and $\tilde{m}$ are both negative and that an increase in the time required to obtain the goods and the medical care is also negative. Finally, an increase in non-labour income y has an ambiguous effect on total medical care consumption. Intuitively, if both C and $\tilde{m}$ are normal goods, an increase in y will lead to an increase in both C and $\tilde{m}$. But the increase in C will in turn lead to a reduction in m, so that the final impact on $M = m + \tilde{m}$ is ambiguous.

4 Econometric Specification

4.1 Model Specification

The model developed in the previous section is cast within a very general framework. In order to adapt the model to the data at hand, several assumptions must be made. First, since no data on consumption is available, attention must be restricted to the demand for health care M (no distinction can be made between m and $\tilde{m}$). Second, the individuals all receive medical care at the same health centre, so there is no variation in prices. Finally, since no data is available on labour earnings, hourly wage rates cannot be computed readily.

All these limitations constrain us to work with a reduced form model. Specifically, we assume that the demand for medical care has the following semi-logarithmic form:

$$M_i = \alpha + \beta ln(\omega_i(T - \psi_i)) + \gamma Y_i + \mathbf{Z}_i \delta, \tag{7}$$

where $\mathbf{Z}_i'$ is a K-dimensional vector of socio-economic characteristics, δ is an appropriately dimensioned vector of parameters, Y_i is permanent income, and γ is a parameter. The inclusion of permanent income, as opposed to labour income, assumes the existence of capital markets that allow individuals to borrow against future income streams to pay for the expenses associated with medical care. No such capital market exists in the communities under study. Instead, individuals have access to an alternative system of credit, the tontine, that plays a role similar to a formal capital market.[1] Hence, the relevant constraint is permanent income rather than labour income.

Equation (7) can be rewritten as:

$$M_i = \alpha + \beta ln\omega_i + \beta ln(T - \psi_i) + \gamma Y_i + \mathbf{Z}_i \delta. \tag{8}$$

The purpose of rewriting (7) as (8) is to allow us to instrument the wage rate with various regressors (set of occupational dummies). Similarly, the travel time required to receive health care can be approximated by the distance to the health centre, conditional on controlling for means of transportation. Finally, permanent income can be approximated with various wealth variables such as type of house (various types of roofs and walls).

4.2 Count Data Models

In our model, the dependant variable, M_i, takes on only non-negative integer values, i.e. the number of visits to the CHC. The modelling of such random counts does not have a long tradition in economics as opposed, say, to biometrics. Nonetheless, a certain number of papers have appeared recently in the economics literature that warrant the use of count models [Cameron and Trivedi(1986, 1990),Cameron, Trivedi, Milne and

Piggot (1988), Gourieroux et al. (1984b), Hausman, Hall and Griliches (1984), Rose (1990), Ruser (1991)]. Essentially, the purpose of using count data models is to avoid the statistical shortcomings of OLS regressions on such data. Indeed, linear regressions do not account for the fact that there is a mass point of observations with $M_i = 0$. Further, they allow predicted values to be negative.[2]

Our empirical strategy follows the suggestion of Cameron and Trivedi (1986) and start from the simple but restrictive Poisson model and moves towards more involved but less restrictive models. First, we assume that the number of visits to the CHC follows a Poisson distribution whose probability density is given by:

$$Pr(m_i) = e^{-\lambda_i}\lambda_i^{m_i}/m_i!, \tag{9}$$

where, here, m_i is the realized value of the random variable M_i. Exogenous variables can easily be incorporated into the model by rewriting λ_i as :

$$\lambda_i = \exp(\mathbf{X}_i\beta), \tag{10}$$

where $\mathbf{X}_i$ is a vector of dimension k and β is an appropriately dimensioned vector of parameters. The likelihood function for this model is

$$L = \sum_i m_i X_i\beta - \exp(X_i\beta). \tag{11}$$

This function can easily be shown to be globally concave and thus converges very rapidly. There are essentially two major drawbacks with the Poisson model. First, it can be shown that the conditional mean of M_i is equal to its conditional variance: $E(M_i|\mathbf{X}_i) = Var(M_i|\mathbf{X}_i)$. This restriction will generally produce underestimated standard errors of the estimators if the data is indeed characterized by overdispersion $[E(M_i|\mathbf{X}_i) < Var(M_i|\mathbf{X}_i)]$ as is typically the case. Fortunately, a number of ways have been proposed to test overdispersion [Cameron and Trivedi (1990)]. Second, the Poisson model assumes that events occur independently over time. In other words, the probability that an individual visits the CHC at time t is independent of the fact that he visited at time $t-1$. Thus the Poisson model excludes altogether the fact that there may be occurrence dependence in the data [See Heckman and Borjas (1980)for a full treatment].[3]

In the absence of such time dependence, the length of the period of analysis can be made arbitrarily large. We thus start by aggregating the eleven-period frequencies into a single one-period frequency. This allows us to decompose the data generating process in a tobit-like fashion. Indeed, as was shown by Mullahy (1986), it is possible to rewrite the Poisson process as a binary outcome (visits vs no visits) and a conditional distribution of the positives. To see this, consider the probability density in (9). It follows that

$$Pr(m_i = 0) \;\; = \;\; (e^{-\lambda_{1i}}\lambda_{1i}^{m_i})/m_i! = \exp(-\lambda_{1i}), \tag{12}$$

$$1 - Pr(m_i = 0) = \sum_{m_i \in \Gamma_+} Pr(m_i) = [1 - \exp(-\lambda_{1i})], \tag{13}$$

$$Pr(m_i | m_i > 0) = \lambda_{2i}^{m_i} / \{[\exp(\lambda_{2i}) - 1] m_i!\}, \quad m_i \in \Gamma_+, \tag{14}$$

where Γ_+ is the subset of individuals with positive counts. Using the parameterization in (10), the generalized likelihood function of the Poisson distribution is:

$$\Lambda = ln\Bigg(\Big[\prod_{i \in \Gamma_0} \{\exp[-\exp(\mathbf{X}_i \beta_1)]\} \prod_{i \in \Gamma_+} \{1 - \exp[-\exp(\mathbf{X}_i \beta_1)]\} \Big] \tag{15}$$
$$\times \Big[\prod_{i \in \Gamma_+} \exp(m_i \mathbf{X}_i \beta_2) / (\{\exp[\exp(\mathbf{X}_i \beta_2)] - 1\} m_i!] \Bigg),$$

where Γ_0 is the sample of individuals with zero counts. Thus the likelihood function can be expressed as $\Lambda = \Lambda^1(\beta_1) + \Lambda^2(\beta_2)$. This likelihood function reduces to (11) in the special case where $\beta_1 = \beta_2$. This decomposition is of particular interest in our case since it allows us to assess whether the parameters that determine the probability of visiting the health centre are the same as those determining the number of times individuals show up for medical care.[4] In the event where $H_0 : \beta_1 = \beta_2$ is rejected (via a Hausman's test), it may be best to concentrate on the positives since otherwise the parameter estimates obtained by various estimators will represent the sum of two processes that can not be as easily disentangled as in the present case.[5] Truncated Poisson models have been studied by Terza (1985). Ideally, such models should be used when concentrating on the positives. However, our empirical strategy consists in moving from restrictive (Poisson) models towards more general count data models that cannot account for truncation. In order to keep the models comparable, we shall not use truncated Poisson models.

Mullahy (1986) has also shown that overdispersion (underdispersion) naturally occurs in the hurdle model (15), and that a test on the null hypothesis $H_0 : \beta_1 = \beta_2$ is implicitly a test on such overdispersion (underdispersion). Yet, even if the null assumption is not rejected, there may still be overdispersion in the data. It is now customary to relax the Poisson assumption by introducing a random component in λ_i by replacing (10) with

$$ln\lambda_i = \mathbf{X}_i \beta + \epsilon_i, \tag{16}$$

where the error term, as in ordinary linear models, represents omitted exogenous variables. It can be shown that if ϵ_i has a gamma distribution whose parameters are ϕ_i and ν_i then the negative binomial model (compound Poisson) results:

$$Pr(m_i) = \frac{\Gamma(m_i + \kappa_i)}{\Gamma(m_i + 1)\Gamma(\kappa_i)} \Big(\frac{\kappa_i}{\kappa_i + \phi_i} \Big)^{\kappa_i} \Big(\frac{\phi_i}{\kappa_i + \phi_i} \Big)^{m_i}, \tag{17}$$

with $E(m_i) = \phi_i$, $Var(m_i) = \phi_i + \phi_i^2/\kappa_i$. Since $\phi_i/\kappa_i > 0$, then $Var(m_i) > E(m_i)$, so that this specification contains overdispersion. To insure non-negativity of the mean, a natural specification is $E(m_i) = \exp(\mathbf{X}_i\beta)$, obtained by letting $\phi_i = \exp(\mathbf{X}_i\beta)$. In this paper we have chosen to specify[6]

$$\kappa_i = \frac{1}{\alpha}\exp(\mathbf{X}_i\beta), \tag{18}$$

so that $Var(m_i) = (1+\alpha)E(m_i)$. The parameter α is sometimes referred to as a 'precision parameter' in the literature. A test on overdispersion thus boils down to a t-test on α.

4.3 Quasi-Generalized Pseudo-Maximum-Likelihood Estimators

The estimators presented so far rely on strong distributional assumptions about the data generating process. For example, if the true distribution of ϵ_i above is not gamma, maximum likelihood estimation of the negative binomial model will produce inconsistent estimators. Gourieroux et al. (1984b) derived conditions under which pseudo-maximum likelihood estimators (PMLE) and quasi-generalized pseudo maximum likelihood (QGPML) estimators of any member of the linear exponential family will be consistent. Essentially, the only requirement is that the conditional mean of M_i be correctly specified for the PMLE and that the conditional variance be further correctly specified for the QGPMLE. The linear exponential family includes the Poisson, negative binomial (κ given), gamma (κ given) and the normal (σ^2 given).

It can easily be shown that the objective function of the pseudo-maximum likelihood function for the negative binomial model is given by

$$\sum_i \{m_i\mathbf{X}_i\beta - (\frac{1}{\alpha} + m_i)ln(1 + \alpha\exp(\mathbf{X}_i\beta))\}, \tag{19}$$

where α is the same 'precision parameter' as above. Similarly, the objective function for the QGPMLE of the negative binomial model is given by

$$\sum_i \{m_i\mathbf{X}_i\beta - (\frac{1}{\hat{\eta}^2} + m_i)ln(1 + \hat{\eta}^2\exp(\mathbf{X}_i\beta))\}, \tag{20}$$

with

$$\hat{\eta}^2 = \sum_i \frac{[(m_i - \exp(\mathbf{X}_i\hat{\beta}))^2 - \exp(\mathbf{X}_i\hat{\beta})]\exp(2\mathbf{X}_i\hat{\beta})}{\sum_i \exp(4\mathbf{X}_i\hat{\beta})}, \tag{21}$$

and where $\hat{\beta}$ are PML estimators. For each case, the appropriate asymptotic variance-covariance matrix is given in Gourieroux, Monfort and Trognon (1984a). Naturally, one can never be 100% sure that the specified distribution for the data is the true one. Nevertheless, if the parameter estimates based on week distributional assumptions (PMLE-QGPMLE) are similar to those based on more stringent distributional assumptions (negative binomial, Poisson), one can reasonably assume that the model is not misspecified. In the event they differ substantially, one should prefer QGPML estimators.

5 Empirical Results

As of may 1987, the population of Pahou-Avlékété amounted to 18,441 individuals. In estimating the different models of the previous section a certain filtering of the data was performed to insure coherency. First, all the records containing missing or misreported data on one of the variables used in the estimation were discarded. Thus 128 individuals did not report their birth year, a problem most likely correlated with age since many old people simply do not know it, or have a very imprecise idea about it. To the extent this is true, our sample will slightly over-represent younger (and more likely healthy) individuals. Second, individuals had to be born at the time of the first census (1983) and still be alive at the end of our period of analysis (1987). This condition is necessary to insure the sample remains constant throughout the period of analysis (balanced panel). As many as 3 015 individuals were born following the first census and over 2,126 individuals died during the same period. Of those who died, 433 did not reach 1 year of age. Thus the infant mortality rate was about 144/1000 during that period, somewhat below the national average of 156/1000 for the same period. Considering all these exclusions, our sample size reduces from 18,441 individuals to 13,112.

As mentioned previously, one basic criticism addressed at count models concerns the adequacy of using counts as a measure of medical care consumption. One could very well argue that due to the qualitative aspects of medical care, frequency of visits simply is an integer measurement of an otherwise continuous variable. There are two ways we circumvent this difficulty. First, we estimate an ordinal probit model as suggested by McKelvey and Zavoina (1975), the details of which are provided below. This allows treating the endogenous variable M_i^* as a continuous latent variable with an observable counterpart given by M_i. Second, we have limited our analysis to the three main diagnostics found in the administrative files of the CHC, namely Fever, Respiratory Infections and parasitic diseases. These three can be considered to require sensibly the same level of care (i.e. the same number of visits). We thus avoid adding visits made for fever with those made for hypertension, say. Furthermore, by concentrating on three simple diagnostics we decrease the likelihood of someone being treated outside the CHC since most alternatives are infeasible (hospital, private clinics in Cotonou, etc.). Traditional practitioners and self-medication remain feasible alternatives, though.

Of the 13,112 individuals left in our sample, 1,663 visited the CHC over the 5-year period for one of the three above diseases. Hence, our parameter estimates are to be interpreted with this in mind. Put differently, of the 11,449 individuals who did not visit the CHC for one of these diseases, a certain number visited for other diseases and still others preferred to be cured elsewhere.

Finally, by concentrating on one single health centre, we avoid the often mentioned problem of measuring the quality of care at different locations (supply) rather than the demand for health care. Indeed, if the quality of care varies from place to place, the price of medical care is not the same even if the money price is [See Deaton (1988) for an interesting discussion].

Our empirical strategy consists in estimating the various statistical models in two steps. First, we use the independence assumption imposed by the Poisson process and add-up the individual frequencies over the 5-year period into a single frequency. This allows us to estimate the model proposed by Mullahy (1986) and various count models. Next, using the sub-sample of individuals who visited the CHC at least once over the 5-year period, we estimate some count models using the eleven-period panel of individual frequencies. This allows us to incorporate a time trend and a dummy shift variable to reflect the price change that was introduced on prescribed drugs in 1984.

Table 3 presents the results of maximizing the various models presented in the previous section. Following the discussion surrounding the model specification in section 3.2, a number of covariates have been included as proxies to various unobserved components of the model. For instance, it is generally reckoned that the quality of the roofs and walls is a sign of wealth in the communities under investigation. We have thus incorporated six dummy variables to characterize the type of house one owns (3 for roof type, 3 for wall type). We have omitted the lowest-valued type, namely straw for roof and bamboo for wall. To the extent health is a normal good, we expect these parameters to have a positive sign. On the other hand, more wealth may signify more consumption and hence, better resistance to illness. So the parameter sign is indeterminate.

In order to use distance as a proxy to travelling time, we must control for the mean of transportation. Dummy variables are thus included for moped, pirogue, car, and other mode (essentially walking). The omitted group is bicycle (most common). In interpreting the parameter estimates one must be cautious, though, since these variables may also proxy wealth. Next, a series of variables are included to approximate the wage rate. All these variables pertain to the type of activities the individual is involved in. To ease interpretation, only the main activity is included. The omitted group is sale of own produce. The variable Tontine represents the amount invested in a 'tontine' on a monthly basis. The parameter estimate is expected to have a positive since savings may play the role of health insurance against expected spells of illness. Region B and Region C are dummy variables representing respectively the plateau and marshlands regions. To the extent these regions are characterized by more prevalent pathenogenic agents, we can expect a positive sign. Furthermore, since the general level of wealth is lower in these two regions as compared to Region A, one might also expect a positive sign through lower consumption level [equation (2)]. On the other hand, although we control for distance, access to the health centre is limited by geographical obstacles that is not captured by distance. Thus these parameters may have a negative sign (this is true mostly for Region C). The distance variable represents the logarithm of the distance from an individual's village to the health centre in kilometres. Finally, we follow Gertler et al. (1987) and interact distance with a wealth indicator. In their work, they found that the price elasticity of demand for medical care decreases as income rises (hence medical care is a normal good).

This variable thus has important policy implications in our model in terms of equitable access to health care. The wealth indicator is the sum of two dummy variables representing respectively whether the individual has enough land to rent parts of it, and whether he rents out houses to non-family members.[7]

Recall that the endogenous variable for the models of Table 3 is the sum of the frequencies over the 11 semesters of available data. Column (1) presents the Poisson estimates. Most parameters are statistically significant at the 5% level or better. This is not surprising since the sample size is relatively large and also because the Poisson model tends to generate spuriously small standard errors. As expected, the frequencies have a U-shaped profile with respect to age. Thus the young and the old seem to consume more health care than those in-between. The dichotomous variable Sex (=1 if female) has a negative parameter. This can indicate either that women have a higher degree of tolerance to illness or that, all else equal, their spells of illness are deemed as not deserving as much care as mens'.[8] The dummy variables for roof-type all have positive signs which indicates that the income effect dominates the consumption (i.e. better immunization) effect. Some wall-type dummies have a negative sign. This is rather surprising given the results on roof dummies.[9]

The dummy variables for the mode of transportation are all positive and statistically significant. To repeat, one must be cautious in interpreting these parameters since they may proxy wealth. The only occupational dummy that remains significant across the different models is 'Salaried Worker'. This result may reflect the fact that labour income is less unpredictable than income accruing from other occupations and therefore increase the demand for medical care. The result on Tontine is consistent with this result; more savings leads to increased demand.

In the Poisson model the coefficients on continuous variables have to be interpreted as the relative increase in $E(M_i)$ following an increase in the exogenous variable. Dummy variables are similarly interpreted as the increase in $E(M_i)$ given the variable equals unity rather than zero. To see this, let $E(M_i) = \exp(\bar{\mathbf{X}}_i\beta + d_{iv}\beta_v)$, where d_{iv} is the variable of interest and $\bar{\mathbf{X}}_i$ is the vector of remaining variables. Then $E[M_i|d_{iv} = 1]/E[M_i|d_{iv} = 0] = \exp(\beta_v) \simeq 1 + \beta_v$, for β_v small. For continuous explanatory variables, $E[M_i|X_{iv} = X_{iv}^\circ + \triangle]/E[M_i|X_{iv} = X_{iv}^\circ] = \exp(\beta_v\triangle)$. Thus according to column (1) of Table 3, a 1000 CFA Franc increase in a tontine leads to a 5% increase in the number of visits to the CHC, and being a salaried worker leads to a 20% increase relative to other occupations.

One interesting result concerns the dummy variables Region B and Region C. The former has a positive sign while the latter has a negative sign and both are highly significant. Recall that Region B has a lower general level of wealth than Region A but higher than Region C, and has easier access to the CHC than does Region C. To the extent these dummy variables are capturing only general wealth and access effects, it seems the lower wealth in Region B dominates the access effect whereas the converse seems true in Region C. This is not very surprising since individuals living in Region B, controlling for distance, have as easy access to the CHC as individuals of Region A. As mentioned previously, access to the CHC is very difficult for individuals of Region C during rainy seasons (one short and one long). The parameter estimate seem to reflect this.

Finally, the distance variable is negative and highly significant. Since this variable is entered in log form, its parameter is the direct effect of an additional kilometre on total frequencies. Hence, the individuals in our sample seem to have a relatively high 'time-price' elasticity. This result is contrary to some of the earlier literature [Akin, Griffin, Guilkey and Popkin (1984),(1986), Heller (1982)] but consistent with more recent research [Dunlop (1987), Gertler et al. (1987), Dor et al. (1987),(1990), Mwabu (1986), Mwabu et al. (1993)]. Note also that the Wealth-Distance variable is positive and statistically significant. Wealthier individuals thus seem to be less sensitive to distance.

The model of column (1) is a standard Poisson model and thus constrains the parameters β_1 and β_2 of equation (15) to be equal. We relax this assumption and report separate estimation results of equation (15) in columns (2) and (3). Column(2) reports the parameter estimates of the binary outcome model (β_1) and column (3) reports those of the conditional Poisson model (β_2). As can be seen, the parameters of column (2) and column (1) are very similar. A Hausman's test can be conducted on the null hypothesis $H_0 : \beta_c = \beta_1$, where β_c is the constrained vector of parameters of column (1). The test yield $\chi^2 = 1.315$ and the critical value is $\chi^2_{.05}(23) = 35.17$. Thus a simple binary model cannot be statistically distinguished from a Poisson model that uses frequencies. This result is most certainly due to the fact that the vast majority of individuals report zero counts.

The parameter estimates of the conditional Poisson model [column (3)] tell a slightly different story from the previous two models. Conditional on having visited the health centre at least once, the frequency of total visits is concave in age rather than U-shaped. Thus households seem to exercise considerable latitude in responding to morbidity that is neither severe nor urgent. It would be worth investigating whether spells that plague children are treated by traditional practitioners or self-medication, if at all. The result of such an investigation may have important policy implications. The results on sex, roof-types, wall-types, mean of transportation, occupations and tontine are similar to those of the previous models. The most striking difference concerns the region dummies. Region B still has a positive and significant parameter estimate. But now so does Region C. Thus it appears from column (1) and (2) that living in Region C is an impediment in securing health care at the CHC. Yet, conditional on visiting the CHC at least once, the individuals of Region C have more frequent visits than those of Region A, presumably because of poorer overall health conditions. The results on Distance and Wealth-Distance are fairly robust across specifications. Finally, a Hausman's test strongly rejects the assumption $H_0 : \beta_c = \beta_2$.

Column (4) reports the parameter estimates of the negative binomial model [equation (17)]. Recall that this model allows overdispersion in the data and thus nests the Poisson model of column (1). As can be seen, the parameters of columns (1) and (4) are very similar. The only difference lies in the larger estimated standard errors of column (4). This conclusion is often reached when comparing Poisson and negative binomial parameter estimates [Cameron and Trivedi (1986)]. In our specification, a test on overdispersion boils down to a t-test on α. So the Poisson estimates must be rejected in favour of the negative binomial model.

Column (5) presents the quasi-generalized pseudo maximum likelihood estimators [equation (20)].[10] Notice that the parameter estimates closely match those of the negative binomial model except for one notable exception, Region C. The QGPMLE of this parameter is positive and statistically significant as in the conditional Poisson model. Note also that the distance parameter is greatest (in absolute value) in this model. This estimator thus appears to weigh more heavily the role played by distance, and as a result Region C now has a positive parameter. This is further evidence that when we control adequately for distance, the poorer individuals of Region C consume more health care than others.

Finally, for the sake of completeness, we report in column (6) the parameter estimates of an ordered probit model. The motivation for this model lies in the fact that the number of visits to the CHC may not be an appropriate measure of health care consumption. Instead one might consider the frequency of visits as an ordinal measure of an unobservable continuous variable. Thus write

$$M_i^* = \mathbf{X}_i\beta + u_i \tag{22}$$

as the underlying model, with $\mathbf{X}_i$ a set of explanatory variables and u_i as the residual. Since M_i^* is not observed, we use the normalization rule that $Var(u_i) = 1$. Thus $u_i \sim N(0,1)$, as in the probit model. We assume that M_i^* and M_i are related as follows. T responses, $R_1, \ldots, R_T$. Let $\mu_0, \mu_1, \ldots, \mu_T$ denote $T+1$ real numbers with $\mu_0 = -\infty$, $\mu_T = +\infty$ and $\mu_0 \leq \mu_1 \leq \ldots, \leq \mu_T$, such that

$$M_i \in R_k \iff \mu_{k-1} \leq M_i^* \leq \mu_k$$

for $0 \leq k \leq T$. Since M_i is an integer variable, it can be represented by a series of dummy variables:

$$M_{ik} = \begin{cases} 1 & \text{if } M_i \in R_k \\ 0 & \text{Otherwise} \end{cases}$$

where $k = 1\ldots, T$. The ordinal probit model leads to the following probability function:

$$Pr[M_{ik} = 1] = \Phi[\mu_k - \mathbf{X}_i\beta] - \Phi[\mu_{k-1} - \mathbf{X}_i\beta]$$

There are thus $dim(\beta) + T$ parameters to be estimated. As shown in column (6), the parameter estimates of the ordered probit model follow closely those of the other models. The ancillary μ parameters reported at the bottom of the table range from 0.424 to 1.787, whereas the observed counts range from 0 to 9.[11] Thus individuals with $M_i^* \leq 0.424$ would record a count of zero, those with $0.424 \leq M_i^* \leq 0.719$ would record a count of one, etc. Qualitatively, then, the conclusion of the ordered probit model are the same as those of the various count models.

The robustness of our parameter estimates increases our confidence in the substantive conclusions that can be drawn from Table 3. The only parameter of interest that changes between specifications is Region C. This reduced form parameter is sometimes dominated by the (poor) wealth effect, and sometimes by the (large) distance effect. We investigate further the theoretical model by concentrating on the individuals who have visited the CHC at least once between 1983 and 1987. Instead of using aggregated frequencies, we use the 11 semester panel of frequencies available in the administrative files. For a typical individual, we observe a sequence of zero and positive counts.[12] There are two main reasons to do this. First, we want to investigate the impact of the 40% increase in the price of prescribed drugs introduced in the first semester of 1984.[13] Second, we want to verify whether there is a tendency to use more the CHC as the experiment became better known in the communities.

Table 4 reports the parameter estimates of several of the same statistical models as in Table 3. Strictly speaking, these parameter estimates are comparable to those of the conditional Poisson model of Table 3 since they are based on the sub-sample of individuals who visited the CHC at least once, even though most individuals have zero counts during the majority of semesters. Notice that the parameters of Table 4 are very similar to those of the conditional model of Table 3. Furthermore, the parameter estimates are remarkably constant across specifications. This adds further confidence that the data is generated by a Poisson-type process. As in Table 3 we must reject the Poisson model in favour of the negative binomial model on the basis of the parameter α. The Trend variable is capturing any trend that may be present in the frequency of visits after controlling for a number of covariates. According to the parameter estimate, there seems to be a 2% increase each semester, which is consistent with the idea that the CHC progressively is becoming the main source of health care in the communities of Pahou-Avlékété. Finally, the Shift variable is a dummy indicator that takes the value 1 if the visit is made after the third semester and 0 otherwise. As can be seen the price increase in prescribed drugs has had a negative and significant impact on the number of visits. Knowing that the price increase was 40%, we can compute an approximate arc price elasticity as $\triangle M\% / \triangle P\% \simeq \beta / \bar{M} = -0.04$. This crude measure suggests that the individuals are not very sensitive to the price of prescribed drugs (which constitutes the total fee). From Table 4 we can thus conclude that the individuals respond to economic incentives: the price elasticity is negative and statistically significant, albeit relatively small; the time price has a negative and substantial impact on primary health care demand. Both these conclusions are robust under the different statistical models that we have considered.

6 Conclusion

The aim of this paper is to provide empirical evidence on the sensitivity of the demand for primary health care in rural Bénin. To this end, we use data from an experiment being conducted in the Pahou-Avlékété area, south of Cotonou.

The main difficulty in using administrative data is that we do not have information concerning consumption of health care outside the CHC. By concentrating our attention on three basic and simple diagnostics (fever, respiratory infections and parasitic diseases), we diminish the possibilities of substitution as some alternatives are clearly infeasible (hospital, private clinics in Cotonou, etc.). Traditional practitioners remain a feasible option to the CHC and our parameter estimates must be interpreted with this in mind.

The essence of our theoretical model rests on the assumption that health is a function of consumption and that the time price of consuming private and health goods must be entered into the budget constraint. Due to data limitations, we must rely on a reduced form model and interpret the parameter estimates accordingly.

In general, most parameter estimates have the expected (structural) sign. For instance, we do observe the postulated U-shaped relationship between age and morbidity in Table 3. Yet, when we use the sub-sample of individuals who have visited the CHC at least once (column (3) of Table 3 and Table 4), we obtain a concave relationship. The same result was obtained by Heller (1982) in studying peninsular Malaysia. It thus appears that households exercise considerable latitude in responding to morbidity that is neither severe nor urgent. One possible explanation is that households turn to traditional practitioners for curative care for their children. The consequences of allowing this morbidity remains an important policy issue. Certainly, further investigation into this problem is warranted.

Our parameter estimates also support the view that wealthier individuals consume more health care and that the poorest regions have increased demands presumably because of lower consumption levels. In line with recent research, we find that distance plays a crucial role in rationing demand for primary health care. Furthermore, wealthier individuals seem to be less sensitive to distance, a result that was found by Gertler et al. (1987) and Mwabu et al. (1993). This has important policy implications in terms of equity. In the context of highly subsidized prices, it is best then to locate the health facilities near the poorer areas.

When we take advantage of the panel dimension of our data, two additional results emerge. First, the number of visits made at the CHC increased steadily throughout the time horizon of the study. This may indicate that the CHC is gaining credibility and is becoming a natural first-line provider. Second, the 40% price increase on prescribed drugs in 1984 has had a small but significant impact on demand. The computed price elasticity is within the range found by Dunlop (1987) when studying health care financing in Ethiopia. Thus there seems to be some room for increasing fees to help alleviate the financial problems that plague the activities of the CHC. To the extent the latter aims at providing primary health care to all, compensation schemes should be envisaged to protect the poor and avoid inducing them to turn to lower quality alternative care.

The robustness of our parameter estimates justifies a certain confidence in the empirical findings. Nevertheless much work remains to be done to better understand the determinants of primary health care demand. For instance, it would be preferable to use a structural model to allow the simulation of different policies. Also, it would be important to introduce adequate measures of health status in the model. In view of our finding on the price-elasticity, it would be important to extend the coverage of the experiment to populations that face different prices and access costs to better assess the sensitivity of the demand to prices.

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Notes

[1] A tontine is a credit system by which individuals make regular (monthly, weekly, etc.) predetermined contributions to a fund administered by a 'tontinier' who invests the fund in different projects. Each contributor receives once at a randomly determined date his contribution plus his share of the yield of the projects. It is not possible to forgo a payment, but it is possible to advance the time at which one receives his due (borrow). Advance payment imposes increased contributions later on (interest charges). The whole system is very informal and rests solely on the mutual confidence of the participants. Typical tontines vary between 10 to 20 participants and last for at most one year. It is the only form of credit in the rural communities in Bénin and probably the most important one in urban areas.

[2]Some authors have argued that count data models may not be appropriate to study the demand for medical care given the qualitative dimensions of the services [Cameron and Trivedi (1986)]. This argument certainly applies when the nature of the visits is not know to the econometrician. Here, we are limiting our investigation to only three basic diagnostics that can be considered homogeneous in terms of physician's time input and intensity of effort. Nonetheless, we provide ordinal probit estimates as a further check of the count data models. Note that the same critic can be addressed at models of car or airline accidents since the gravity of the accidents (incidents) is a continuous rather than discrete variable.

[3]Autocorrelation in the residual because of individual fixed effects. Hausman et al. (1984) have proposed a fixed effects version of the negative binomial model which was recently used by Ruser (1991).

[4]In our administrative file we naturally have no information on those individuals who have decided to by-pass the VHA-CHC system during the 11 semesters covered by the study. In order to estimate the extent of the phenomenon, a survey was conducted in the Pahou-Avlékété region in 1986 in which the individuals were asked whether they had been sick in the past 14 days and if so, which of five possible facilities they had consulted. Of the 579 individuals reporting having been sick, 228 visited the VHA-CHC, 151 used self-medication, 148 consulted a traditional healer, and 24 went to the hospital in Cotonou. This distribution of choice may not pause as serious a problem as may seem. According to the VHA that we consulted, most individuals start by using self-medication or by seeing a traditional practitioner. If the symptoms persist, they automatically visit the VHA-CHC. In other words, the majority of individuals who have been sick during the period of analysis have visited the CHC. This is also evidenced by the fact that 6,973 individuals out of 18,441 visited the CHC at one time between 1983

and 1987.

[5] Heller (1982) estimates separately a logit model to determine whether outpatient care are sought at all and a least squares model on the number of visits made at different facilities. Hence, no account is made of the fact that limiting the analysis to the positives may introduce a bias.

[6]Obviously there are many possible parameterization for κ_i . See Winkelman and Zimmerman (1991b),Winkelman and Zimmerman (1991a) and Ruser (1991) for more general specifications.

[7] This indicator clearly is arbitrary. We experimented considerably with different indicators and different scalings and the results turned out to be fairly robust.

[8] This interpretation was suggested to us by Dr. Félicien Houyé from CREDESA.

[9]One possible explanation for this result suggested by researchers at the CHC goes as follows. In the marshlands (Region C), the wealthiest individuals are Ghanaian merchants who have settled in the area. The local natives do not consider their settlement as permanent and thus do not tolerate these individuals building houses made of cement or clay walls; they are constrained to use 'cheap' bamboo walls as an indication that they do not intend to stay for long. Since it is not possible to identify these individuals in the sample, no attempt was made to account for this.

[10]For the sake of brevity, pseudo-likelihood estimators are not reported but are available upon request.

[11] Some individuals had counts higher than 9. Their frequencies were truncated at 9 and no adjustment was made in the likelihood function since there were too few individuals in this situation.

[12]The visits are not dated within the semesters. So it is not possible to investigate the presence of clusters within semesters or investigate the length between spells.

[13]This price increase was made necessary to pay the VHA. At the beginning of the experiment the VHA worked on a volunteer basis.

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