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DISCRETE CHOICE ESTIMATION OF PRICE-ELASTICITIES: THE BENEFITS OF A FLEXIBLE BEHAVIORAL MODEL OF HEALTH CARE DEMAND

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ABSTRACT

Previous literature on discrete health care demand estimation has used a wide range of different specifications, and results may be sensitive to model choice. This paper advocates a flexible behavioral model of discrete choice health care demand which nests previous models, enabling them to be structurally interpreted as well as tested against one another. Based on testing of data from Côte d'Ivoire, it is found that certain recognized restrictions on income variables appear to have little impact on results. However, the specification of the price variable can have large impacts on policy inferences. The flexible model ameliorates this sensitivity, and allows structural interpretation when the data rejects more restrictive models.

KEY WORDS: Health Care Demand, Discrete Choice Estimation, Flexible Behavioral Model

SECTION 1: INTRODUCTION

Behavioral health care demand models provide important information for the evaluation of potential health care policy reforms. However, the exact empirical implementation of demand estimation with discrete data has become a point of contention between researchers. Jimenez (1995) reviews studies of discrete choice health care demand in developing countries, and concludes that the methods and results have been sufficiently varied so as to make general policy conclusions uncertain. The present paper resolves some sources of this uncertainty.

The importance of allowing flexible regression specifications has been emphasized by numerous authors, such as Leamer (1983). A flexible behavioral model of discrete choice health care demand is proposed here, to provide a theoretical framework for testing implicit assumptions, and comparing alternative approaches to specification. One type of restriction considered here, which is typically used in discrete choice analysis even though it has been rejected empirically in continuous models, arises from additive separability in the utility function. Also explored are simplifying restrictions in the budget constraint, including often omitted cross-price effects. In addition, the specification of the time cost of demanding health care goods is analyzed.

The paper is outlined as follows. Section 2 reviews past structural models of discrete choice demand, and their application to health care. Section 3 then explores theoretical justifications for relaxing assumptions implicit in past work. Section 4 describes the characteristics of a flexible model which jointly relaxes these assumptions. Section 5 uses this flexible model to contrast and interpret previous models, and then demonstrates the importance of flexibility in Cote d'Ivoire health care demand data.

Empirically, it is shown that results can be sensitive to the specification chosen. Constraining price variables across discrete alternatives is strongly rejected, and can have large effects on elasticities. The specification of income, which has been controversial, does not appear to affect estimates greatly. This indicates that while Gertler and van der Gaag (1990) were justified in imposing income restrictions for parsimony, earlier linear models also appear justified empirically (as well as theoretically, as shown in the model). However, significant differences in explanatory power and in policy-relevant parameters are found overall when the more flexible model is used.

In particular, the hospital travel time elasticity in the parsimonious specification is approximately -.5, significant, and larger than the clinic elasticity. However, the flexible model estimates this elasticity at -.1 and not statistically different from zero. Such differences are important given the policy focus on whether people will respond to changes in health care access and user fees. The flexible specification may also be preferred in estimating discrete choice demand models of health care with other data, as well as discrete choice demand models of other goods.

SECTION 2: DISCRETE CHOICE THEORY AND EMPIRICAL SENSITIVITY

2.1 Previous Structural Modeling

McFadden (1981) presents his economic justification of the multinomial logit model using an indirect utility function V, which is conditional on choosing alternative j. Individuals choose j iff $V_j >= V_k$ for all k in the set of options J. Indirect utility depends on variables such as income Y, price p_j and attributes w_j of the discrete alternative chosen, prices r of other goods, and individual characteristics s: $V(Y-p_j, w_j, r, s)$. Furthermore, for much of the analysis McFadden assumes an additively separable functional form: $V_j = Y - p_j - \alpha(r, w_j)$.

This model has been adapted to discrete health care choices by Gertler et al. (1987). They represent conditional utility as an additively separable function of health H and non-health consumption C when j is chosen: $U_j = \alpha_1 C_j + \alpha_2 C_j^2 + \alpha_4 H_j$.[1] Utility is

[1] The indexing of coefficients alpha is purposely not consecutive in this section. Implicitly many zero restrictions are assumed, and the indexing corresponds to the coefficients in the more flexible model presented below, which nests this one.

maximized subject to a budget constraint $Y=C_j+p_j$, and the health production technology which depends on initial health status H_0 and the health improvement Q_j from health care choice j: $H_j=H_0+Q_j$. This leads to a conditional indirect utility function similar to McFadden's:

$$(1) \quad V_j = \alpha_1(Y-p_j) + \alpha_2(Y-p_j)^2 + \alpha_4(H_0+Q_j).$$

The quadratic consumption term is added because Gertler et al. considered the linear utility approximation to be overly restrictive for their application, in that it did not allow price elasticities to vary directly with income. This flexible generalization, as well as others added below, are still justified in McFadden's framework:

> "Since any continuous (indirect) utility function can be approximated ... to any desired degree of accuracy by an appropriate linear-in-parameters specification ... z_i (the vector of explanatory variables of choice i) can incorporate complex transformations and interactions of the raw data (McFadden, 1981 page 220)."

The health production function is further specified by Gertler et al. as depending on a vector of individual characteristics X, whose effect on health may vary with the choice. A constant γ_0 is also included, which McFadden argued serves to capture unobserved elements of each choice: $Q_j= \gamma_{0j} + \gamma_{1j}X$.

Note that because the initial health status H_0 does not vary across choices, and its effect was not specified as differing across choices, H_0 can be omitted from the indirect utility specification. The same is true of the linear and quadratic income terms, leading to Gertler et al.'s parsimonious estimating equation:

$$(2) \quad V_j = \alpha_1(-p_j) + \alpha_2(p_j^2 - 2p_j{*}Y) + \alpha_4\gamma_{0j} + \alpha_4\gamma_{1j}X$$

This could be alternatively written as:

$$(3) \quad V_j = \beta_{0j} + \beta_{1j}X + \beta_2 p_j + \beta_3 p_j^2 + \beta_4 p_j{*}Y, \text{ where } \beta_4 = -2\beta_3$$

Assuming a multinomial logit model, the resulting elasticity of the probability D_j of choosing alternative j, with respect to price j, is then: $E_j^j = D_jD_k[\beta_2 - 2\beta_3(Y-p_j)]$.
For non-zero α_2 this price elasticity depends on income, giving the desired flexibility.

This can be contrasted with the linear specifications often estimated in discrete choice health care demand models (eg. Akin, 1985; Dor and van der Gaag, 1993; Lavy and Quigley, 1993; Lavy, Palumbo and Stern, 1993; and Mwabu, Ainsworth and Nyamete, 1993):

$$(4) \quad V_j = \beta_{0j} + \beta_{1j}X + \beta_{2j}p_j + \beta_{5j}Y$$

which yields an own-price elasticity of $E_j^j = D_jD_k[\beta_{2j}]$.

Note, however, that the Gertler et al. model does not nest this common linear model, because the former does not allow separate alternative-specific coefficients on income (or prices). Gertler et al. argued that allowing alternative-specific income coefficients would actually violate rational choice axioms. In general, however, McFadden (1981) provides a simple justification for allowing income coefficients to vary by choice: He notes that tastes (for each alternative) may depend on individual characteristics that are correlates of current income, such as historical wage rates and income levels. Typically income is measured only by its correlates, such as household consumption, and in such cases McFadden's argument justifies estimating different coefficients on income for each alternative. This issue will be further explored in Section 3.

2.2 Assessing Empirical Sensitivity

Empirical evidence discussed below for the sensitivity of results to specification is presented in Table 2, which compares hospital and clinic own time-price elasticities from the models estimated in Tables 3-9 (regressions are referred to as T.C, for example 3.1 refers to the regression in Table 3 Column 1). Nested tests help determine which specification assumptions are most important, and comparisons are made relative to two basic models: The "linear" model in equation 4 (regression 3.2), and Gertler et al.'s "parsimonious" non-linear model in equation 3 (regression 3.1), referred to as the *linear* and *parsimonious* models, respectively. Tables also include the effects of imposing each assumption type on the "flexible" model which is advocated in Section 4.

The data used are the 1985 Cote d'Ivoire Living Standards Survey, a multi-purpose survey of 1600 households from a national random sample. See Ainsworth and Munoz (1986) for details of the survey, and Dow (1995) for details of the specific sample used here. This same data has been used in several health care demand studies with differing specifications (eg., Gertler and van der Gaag, 1990; Dor and van der Gaag, 1993), and is used here for comparability with these past studies. Like in other studies the sample used is restricted to rural households, and includes only adults having reported themselves sick[2].

Means for the data are reported in Table 1. People are assumed to choose between hospital care, clinic care, or "self care." No fees were charged for health consultations in Cote d'Ivoire in 1985, thus the price is simply the time-price. Travel times to the closest hospitals and clinics were reported by community elders in each survey cluster. These were used along with community reported wages, to ameliorate endogeneity of self-reports.

All regressions were estimated as 3-choice nested logits, allowing correlation between hospital and clinic unobservables, thus assuming that they are nested separately from the "self care"

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[2]Dow (1995) investigates possible selection bias from conditioning on sickness, and finds estimates are not biased. However, they can only be interpreted as "short-run" demand.

option. Estimation was carried out with Axel Boersch-Supan's (c) "HLogit" program, using full information maximum likelihood. Davidson-Fletcher-Powell was employed as the numerical optimization algorithm, with the final covariance matrix re-calculated with the exact hessian. The self-care coefficients were normalized to zero in all regressions for identification. Elasticities were calculated by simulating choices after raising travel times by 1% in the data, and calculating the average of individual differences in predicted probabilities (Train, 1985).

Preliminary evidence of the sensitivity to specification is seen by comparing the elasticities in Table 2 of the parsimonious (3.1) and linear (3.2) specifications. The parsimonious hospital elasticity of -.46 is significantly different from zero and larger than the clinic elasticity. However, in the linear model this drops to -.11, and it is both insignificant and smaller than the clinic response.

SECTION 3: RELAXING THE IMPLICIT RESTRICTIONS

This section explores restrictions which have implicitly been included in the above specifications, and proposes behavioral justifications for relaxing them. First, a notational device must be introduced, which more clearly indicates why separate alternative-specific coefficients and intercepts may be allowed in the health production function. As explained, the health intercept γ_{0j} in equation 2 may vary by choice because it is an estimate of the unobserved health improvement provided by choice j. Here γ_{0j} is renamed Q_j^b, to represent the basic quality of health care choice j, before being modified by other attributes such as X. Likewise, rename γ_{1j} as Q_j^x, to indicate that it represents how the basic health improvement Q_j^b is modified by characteristic X (eg., a doctor visit may be more productive for an educated person who can better follow a doctor's orders). Thus write the health *improvement* function as:

$$(5) \quad Q_j = H_j - H_0 = Q_j^b + Q_j^x X$$

This notational device is useful in describing additional more complex interactions with health improvements in the utility function.

3.1 Additive Separability in the Utility Function

One restriction which has been strongly rejected in continuous demand modeling is that of additive separability of utility arguments. After surveying the available empirical evidence, Deaton and Muellbauer (1980, page 140) conclude that, "...separability and additivity are too strong to be used in empirical work, despite their undoubted econometric advantages."

In discrete choice modeling, however, such separability is commonly assumed. The effects of this assumption can be examined in the health care demand model presented above, by including an interaction term $C_j*Q^c_j$ between consumption and health improvements in the utility function. This captures the idea that the rich and poor may place different values on improvements in health status.[3] Cameron et al. (1988), and Viscusi and Evans (1990) both provide evidence for the analogous idea that the effect of income on utility may vary with health, and possibly in unanticipated ways.

Note that the health improvement Q^c_j from choice j is superscripted by c. This is because health is multidimensional, with different dimensions being important through different channels. Health aspects which affect the marginal utility of non-health consumption may differ from the health aspects which enter utility separably. The practical implication of this is that the parameterization is more flexible, since it is not necessary to impose restrictions across the additive and interacted health parameters.

The simplest specification of the consumption aspects of the health improvement function is to estimate the health improvements with solely choice-specific intercepts (which for notational ease can be written simply as Q^c_j). This leads to the indirect utility specification:

$$(6) \quad V_j = \alpha_1(-p_j) + \alpha_2(p_j^2 - 2p_j*Y) + \alpha_4\gamma_{0j} + \alpha_4\gamma_{1j}X + \alpha_6(Y-p_j)*Q_{jc}$$

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[3]An alternative test would interact consumption with health itself, but that raises difficult issues in measuring the absolute health status. In the simpler case of interacting with health improvements, the absolute health status differences out of the estimating equations.

Further flexibility could be added to the specification by also interacting the consumption quadratic with $Q^c{}_j$. With these additions, the resulting estimating equation is then more concisely written as:

$$(7) \quad V_j = \beta_{0j} + \beta_{1j}X + \beta_{2j}p_j + \beta_{3j}p_j{}^2 + \beta_{4j}p_j{*}Y + \beta_{5j}Y$$

$$\text{where } \beta_{4j} = -2\beta_{3j}$$

Relaxing the additive separability implies that both income[4] and price terms may be estimated with separate alternative-specific coefficients.

The empirical impact is seen in the Table 2 elasticities corresponding to regressions in Tables 4 and 5. Regression 4.1 relaxes the income constraint in the parsimonious non-linear model, yielding travel-time elasticities which are virtually unchanged from the basic parsimonious regression 3.1. This suggests that the inclusion or exclusion of alternative-specific income variables is not a serious source of mis-specification.

Constraints across price coefficients, however, do appear important. Regression 5.2 relaxes the restriction that the price (wage*time) variables in the parsimonious specification have equal coefficients, and this leads to a more than 50% drop in the

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[4]This specification suppresses a possible quadratic income term, which would be identified by the interaction with the health improvement intercept. Because tastes may be correlated with income, the income quadratic may be zero even when the coefficients on the price quadratic and price*income interaction vary across alternatives.

hospital travel-time elasticity. There is a similar effect when constraining to equality the hospital and clinic coefficients on the travel time component of the price in the linear model (regression 5.3). The hospital elasticity triples, now appears significantly different from zero, and is estimated to be larger than the clinic elasticity.

Furthermore, Likelihood Ratio (LR) tests confirm the statistical significance of these model differences. For the parsimonious test, the chi-squared value of minus two times the log-likelihood difference is 39, which is well above the 99% critical value of 9.2 with two degrees of freedom. Similarly, the LR statistic is 23.4 in the linear model, with only one degree of freedom.

As in continuous demand models, additive separability of the utility specification does appear to be strongly rejected by the data. This is true both statistically, and in terms of the sensitivity of economic inferences from price elasticities.

3.2: Parameterizing the Budgeting Period

Another potential area for adding flexibility to discrete choice demand models is in specifying the components of the consumption variable, which McFadden (1981) represented as $Y-p_j$. Following Gertler et al. (1987), consumption in the current period t (following the input choice) can be more generally written as: $C_{j,t} = \lambda Y - p_j$. Here λ is an unknown parameter representing the budgeting period for the income Y from which the health care price

p_j is subtracted. If annual income is used in the estimation, but families actually budget health care expenses from monthly income, for example, then without the λ parameter the income and price elasticities would be incorrect.

The empirical effect of modeling an unobserved λ parameter is to allow the quadratic consumption term's income and price coefficients to differ in the estimation. The $\alpha_2(\lambda Y-p_j)^2$ term of equation (1) now expands to ($\alpha_2 p_j^2$ - 2$\alpha_2\lambda p_j$*Y), which has the effect of relaxing the β_4=-2β_3 restriction in equation 3.

This device was used by Gertler et al. (1987) to test whether assuming a specific λ-value could be rejected against unconstraining the two coefficients. More generally, this λ value need not be assumed a priori. In some models it can be estimated based on the relationship between the parameters on Y and p. In other models λ may not be recoverable, but that will not bias estimation of the total price and income effects; on the contrary it will only improve those estimates.

In the Cote d'Ivoire data, the effect of the implicit λ=1 constraint is complex. When the parsimonious model is estimated without it (estimating β_3 and β_4 separately) in 7.1, the LR test rejects the constraint, but elasticities change little. However, a bigger economic difference is seen in regression 7.3 when this budgeting constraint is relaxed jointly with also relaxing the separability constraint tested in regression 5.2. In this case, the hospital elasticity drops another 35% from its level in 5.2, and the clinic elasticity drops over 60%. Again, LR tests confirm the statistical significance of rejecting the λ=1 budgeting parameter constraint.

3.3: Future Expectations, and Cross-Price Effects on Utility

An implicit constraint which has received empirical attention, but without theoretical foundations, is whether the price of choice k should enter the utility of choice j. Some applications assume that allowing such cross-price effects would be a mis-specification. For example, Dor and van der Gaag (1993) estimate a linear model which includes cross-price coefficients, but state that, "while our specification is convenient it is not consistent with the random utility maximization framework developed by McFadden."

However, any discrete choice demand model can theoretically incorporate cross-price variables, by assuming forward-looking behavior. Modeling this effect does not require explicitly specifying the dynamic objective and budget constraints. Instead the price of choice k can be another element of the price vector of "other" goods r specified in McFadden's (1981) original work. In the health care demand application considered here, this can be interpreted as a person's choice to visit a clinic today depending on the price of referral visits to hospitals tomorrow.

Let $E[q_j^k]$ be the probability of a future visit to provider k, following today's health care choice j. The expected health improvement $Q_{j,t+1}=E[H_{j,t+1}-H_{j,t}]$ in the next period after choice j may then enter utility directly. A next-period future consumption term may also be specified as: $C_{j,t+1} = \lambda Y - E[q_j^{\,j}]p_j - E[q_j^{\,k}]p_k$. This then leads to the estimating equation:

$$(8)\quad V_j = \beta_{0j} + \beta_{1j}X + \beta_{2j}p_j + \beta_{3j}p_j^2 + \beta_{4j}p_j{*}Y + \beta_{5j}Y + \beta_{6j}p_k$$

Empirically, the inclusion of cross-price variables in the nested multinomial logit estimates of Table 6 have some affect on the linear (regression 6.2) and parsimonious (regression 6.1) models. Dor and van der Gaag (1993) find even larger impacts on cross-elasticities (changes of up to 90%) in their linear model using this same data. However, that may partially be due to the fact that they estimate a non-nested multinomial logit (MNL). Introducing cross-prices into the model is an alternative way (besides the nested MNL) to relax the Independence of Irrelevant Alternatives (IIA) restriction of the MNL. The effect of IIA is to introduce a mechanical relationship between the cross-price elasticity $E_j^{\,k}$ of choice j, and the own-price elasticity $E_k^{\,k}$, when the $\alpha_5=\alpha_5=0$ restriction is imposed:

$$(9)\quad E_j^{\,k} = -E_k^{\,k}D_k/(1-D_k)$$

This IIA restriction has been argued to be restrictive in other contexts. With the above intuition providing a structural foundation, and the empirical importance demonstrated, cross-price restrictions should be routinely tested.

3.4 Opportunity Cost of Time

The full price of many goods is the sum of pecuniary fees F and the opportunity cost of time, the latter of which depends on both the time T spent and the value w of that time:

$$(10)\quad p_j = F_j + \delta w^* T_j$$

Measurement of T and w, however, is difficult. Often w is proxied by the market wage, but this may be a systematic over-estimate if there is unemployment or unmeasured seasonality in the marginal product of labor. Travel time is also problematic, because if somebody has to travel to a commercial area anyway to go to market for example, then the *marginal* travel time may also be systematically over-estimated (this point has also been made in Akin et al.'s (1985) discussion of Miners (1979)). Because of these problems, a unit change in the measured w*T may not equal a dollar change in F, as it should in theory. To take this into account in the estimation, the separate parameter δ is specified above, and allowed to differ from unity. The implication of this is that w*T may be estimated with a different coefficient than the Fee variable.

In addition, it may be desirable to also estimate separate coefficients for both the wage and travel time variables, but for different reasons. For wages, this is because they may enter the choice specification for another reason besides the cost of time to seek care: they also affect the cost of remaining ill. Let

$E[A_{jt}]$ be the expected work absenteeism in the period after choosing health care option j. This enters next period's expected consumption term:

$$(11)\quad C_{j,t+1} = \lambda Y - E[q_j^{\,j}]p_j - E[q_j^{\,k}]p_k - w^*E[A_{jt}]$$

Expected absenteeism is very difficult to measure, and in general it may be approximated simply as an alternative specific dummy interacted with the wage. If expected absenteeism varies across the choices, then this indicates that the wage should be specified as a separate independent variable, estimated with alternative-specific coefficients.

It was proposed above that travel time should also be estimated as a separate variable, and the justification for this is based on the health production function. Traveling for long periods by foot or on a crowded bus over unpaved roads may cause further health damage to infected and weakened individuals. The importance of this effect may be thought to depend on how well the type of facility can treat the health problem, represented by an interaction of travel time with an alternative specific intercept Q_j^T for the particular dimension of health related to traveling stresses. A person may be willing to put up with a tiring long trip if the expected health benefits are large, but may not be willing to do the same for minor expected benefits. Thus a term $Q_j^T T_j$ can be added to the health improvement function (5). The empirical implication of this is that travel time may be specified as impacting utility apart from the opportunity cost of time, and this estimated effect may vary across alternatives.

In the Cote d'Ivoire data, elasticity estimates do appear to be sensitive to how time and wages are specified. When time was added to the parsimonious model (with separate alternative-specific coefficients), the hospital elasticity in Table 2 is seen to drop from -.46 down to -.15 (regression 8.1). If instead time was included as a separate variable, but its effect was constrained to equality across alternatives (regression 8.2), the hospital elasticity remains at -.47. Thus not only does travel time have an effect independent of the opportunity cost of time, that effect may differ depending on the expected quality of health care received. Furthermore, adding a time*wage interaction to the linear specification increases the hospital elasticity estimate from -.11 to -.27 (regression 8.3), which is now significantly different from zero. It appears that linear terms in travel times and wages, as well as a wage*time interaction, are all necessary in a flexible model, in order to accurately capture travel-time elasticities.

SECTION 4: A FLEXIBLE DISCRETE CHOICE DEMAND SPECIFICATION

The above discussion has outlined ways in which conventional health care demand specifications may be made more flexible. The following equation gives the structural conditional utility function resulting from jointly relaxing all of the above restrictions:

$$(12)\quad U_j = \alpha_1 C_{j,t} + \alpha_2 C_{j,t}^2 + \alpha_3 E[C_{j,t+1}] + \alpha_4 E[Q_{j,t}] + \alpha_5 E[Q_{j,t+1}] + \alpha_6 C_{j,t}{*}E[Q^c{}_{j,t}] + \alpha_7 C_{j,t}{}^2{*}E[Q^c{}_{j,t}] + \epsilon_j$$

In accord with the uncertainty described in section 3.3, this is now written with time subscripts, and includes expectations to indicate the uncertainty of consumption next period, and of health both this period and next. The resulting indirect utility function and estimating equations are given further below.

Note first, however, that this model could be extended in many ways. For example, if each of the health improvement functions Q included socioeconomic characteristics X, and each utility term was fully interacted with such a Q function, then estimation could be stratified on the X characteristics. In addition, higher order terms in consumption and health could also be included in the empirical specification of the general utility function $U_j=f(C_j,H_j,\epsilon_j|X)$.

The previous section argued that structural interpretations for flexible discrete choice specifications are readily available. Any final application may want to impose more structure for parsimony and tractability, but this should not be done without exploring the impacts of simplifying econometric restrictions on policy parameters.

4.1: Indirect Utility Function and Estimable Parameters

The model above contains some structural parameters which cannot be identified separately from one another, although their combined effects can be estimated. This is particularly true for the health production parameters, which often will not be recoverable by themselves without imposing considerably more structure. The following equation rewrites the model, substituting constraints into the utility function to derive the indirect utility as a function of estimable parameters:

$$(13)\quad V_j = \beta_{0j} + \beta_{1j}X + \beta_{2j}p_j + \beta_{3j}(p_j)^2 + \beta_{4j}(p_j{*}Y) + \beta_{5j}Y + \beta_{6j}p_k + \beta_{7j}T_j + \beta_{8j}w + \epsilon_j$$

where:

$$\beta_{0j} = \alpha_4 Q_j^{\,b} + \alpha_5 E[Q_{j,t+1}]$$

$$\beta_{1j} = \alpha_4 Q_j^{\,x}$$

$$\beta_{2j} = -\ \alpha_1 - \alpha_3 E[q_j^{\,j}] - \alpha_6 Q_j^{\,c}$$

$$\beta_{3j} = \alpha_2 + \alpha_7 Q_j^{\,c}$$

$$\beta_{4j} = -\ 2\alpha_2\lambda - 2\alpha_7\lambda Q_j^{\,c}$$

$$\beta_{5j} = \alpha_6\lambda Q_j^{\,c}$$

$$\beta_{6j} = -\ \alpha_3 E[q_j^{\,k}]$$

$$\beta_{7j} = \alpha_4 Q_j^{\,T}$$

$$\beta_{8j} = -\ \alpha_3 E[A_j]$$

Notice that terms not varying across alternatives have been suppressed, such as the linear income, and H_{t-1} variables. Also, "conditional" variables (characteristics which vary across choices) have been subsumed by the terms which model such variables as having different marginal effects on different alternatives. For example, the α_1 parameter on consumption is not separately identified, because in the consumption*health interaction, the alternative-specific health quality intercept is unobserved and must be estimated from the data. Again, price is specified here as $p_j = F_j + \delta w^*T_j$. In the common case where there are no out-of-pocket fees, the observed price is simply the w^*T_j interaction, and δ cannot be estimated separately from the price parameters.

Furthermore, for variables which do not vary across the alternatives, identification requires that one of the j parameters be normalized. Thus for some choice k, $\beta_{0k}=\beta_{1k}=\beta_{5k}=\beta_{8k}=0$. The scale of latent utility also must be normalized, which is typically accomplished by setting $E[\epsilon_k]^2=1$.

As written, the model implies no further restrictions on the parameter vector β. Imposing additional assumptions, such as specifying a value for κ, would however imply a number of constraints between parameters which could simplify the estimation.

The fact that certain structural parameters are not estimable may appear to be a drawback of this model. However, this is only true in a limited sense. Economists have stressed the importance of identifying structural parameters (eg., Haavelmo, 1944), but this should not take priority if it involves imposing invalid parameter restrictions. It is preferable to estimate a combination of structural parameters jointly, acknowledging some loss in predictive efficiency, than to force incorrect estimation of structural parameters through inappropriate assumptions.

4.2: Comparative Static Predictions of the Flexible Model

It is of interest to know a priori whether the expected signs of policy variables may be affected by allowing flexible specifications. For the flexible model presented above, given reasonable assumptions on underlying utility parameters, many of the predicted signs are exactly the same as in other models in the literature (see Akin et al., 1985 for comparative statics of many earlier models). The exact comparative statics are presented in the Appendix, but they are summarized here.

One of the important differences from the parsimonious model is that the prices of different alternatives may have very different effects, although all are expected to decrease own demand. Similarly, higher income may increase the demand for some health inputs, but *decrease* demand for others, as people switch to higher quality inputs. Another feature of the flexible model is that wages not only affect the opportunity cost of time spent seeking care in this model, but also the opportunity cost of being sick, through absenteeism.[5] Thus the effects of wages on demand

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[5]The total effect of wages may also be even more complicated than specified here, due to the income effect of higher wages. This has been emphasized in health care demand modeling by Akin (1985). This total effect of wages is rarely estimated, however, since income is usually held constant in the estimation by

are theoretically ambiguous, as earlier models had predicted, but in contrast to recent modeling efforts.

SECTION 5: RECONCILING DISCRETE CHOICE DEMAND MODELS

This section first explicitly shows the restrictions embodied in the previously used linear and parsimonious specifications, and shows that the linear model can be interpreted structurally. Next, general guidelines for model choice are suggested. These guidelines are then illustrated through systematic testing with the Cote d'Ivoire data.

5.1: Linear Utility Model

The most commonly estimated discrete choice health care demand model is one which implicitly specifies utility as a linear function of consumption and health. This is found for example in the work of Akin et al. (1985), Mwabu, Ainsworth and Nyamete (1993), Dor and van der Gaag (1993), Lavy and Quigley (1993), Lavy, Palumbo and Stern (1993). The coefficients typically estimated are: $\beta_{0j}, \beta_{1j}, \beta_{2j}, \beta_{5j}$ (wage variables are often missing, thus T is substituted for T*w in the price). In the notation of the flexible model above, the following implicit restrictions can be inferred on the structural coefficients: $\alpha_2=0$, $\alpha_3=0$, $\alpha_5=0$, $\alpha_7=0$ (although the exact restrictions vary slightly by model).

Gertler et al. (1987), however, pointed out a potential

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including it as a regressor.

problem with this specification. It is seen below though, that this problem disappears if the linear model implicitly assumes a consumption*health interaction. Gertler and van der Gaag (1990, page 66) illustrate the potential problem with a simple example in which people choose between 2 alternatives j and k:

$$(14)\quad U_j = \beta_{5j}Y + \beta_{2j}P_j + \alpha_1 H_{j,t} + \epsilon_j$$

where $\beta_5 = \alpha_1\lambda,$ and $\beta_2 = -\alpha_1$.

Option j will be chosen if $(U_j - U_k) > 0$, which can be written as:

$$(15)\quad (\beta_{5j} - \beta_{5k})Y - \alpha_1(p_j - p_k) + \alpha_1(H_{j,t} - H_{k,t}) > \epsilon_k - \epsilon_j$$

They point out that even if the two prices are the same, and the health outcomes are the same for the two choices, the two choices yield different predicted utilities if $\beta_{5j} \neq \beta_{5k}$ in the estimation,[6] since α_1 does not vary across choices. They implicitly assume that $E[\epsilon_k - \epsilon_j] = 0$, thus ruling out McFadden's unobserved taste argument mentioned in section 2.1. Because in this model utility is only affected by health and other consumption (which is the same in the two choices), it should be that people are indifferent between the two options. This insight led Gertler and van der Gaag to claim that under this model, "preferences are not ordered and

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[6]They do not point out the corollary to this argument, that under this model alternative-specific price-coefficients also cause the same problem, i.e. when $\beta_{2j} \neq \beta_{2k}$ in the estimation.

transitive, and stable utility functions do not exist." They then argue that since the specification is inconsistent with utility maximization, results from it cannot be interpreted structurally (p.100).

However, such estimates can be structurally interpreted if the economic model is expanded slightly to allow α_6 to differ from zero in the estimation. In this case,

$$(16)\quad \beta_{5j}-\beta_{5k} = \alpha_6\lambda(Q_j^c-Q_k^c)$$

implying that income can have different coefficients across choices. Notice that if the health improvements are the same, $Q_j^c-Q_k^c$, then predicted utility will be the same for the two choices. Thus by slightly changing the underlying structural model, these linear estimates can be interpreted as arising from rational choice.

5.2: Parsimonious Non-linear Utility

As an alternative to the linear model, Gertler, Locay, and Sanderson (1987) suggested the "parsimonious" non-linear model. This is also nested by the flexible model, by assuming that α_3=0, α_5=0, α_6=0, α_7=0, and λ=1. Thus the estimated parameters are β_{0j}, β_{1j}, β_2, β_3, β_4, with the constraint that $\beta_4=-2\beta_3$. Notice that by assuming no interaction between health and consumption, $\beta_{ij}=\beta_{ik}$ for i=2,3,4.

5.3: Guidelines for Model Choice

In determining a specification for a given data set, it has been shown above that while economic theory may provide some guidance, structural models are flexible enough to accommodate many possible specifications. It is important to note that the models discussed in earlier sections are not "competing" in the sense of providing very different predictions. The comparative static results generally yield similar information on the signs of important policy variables. The essential question then, is how to find the most parsimonious specification whose simplifying assumptions do not impose empirically invalid restrictions which bias estimation of policy parameters. This involves three objectives:

1. Finding the "best fit," or the equation with the most explanatory power that still can be justified by a flexible version of the structural model.

2. Minimizing the number of parameters for tractability in estimating the highly non-linear discrete choice models, and to ameliorate multicollinearity.

3. Maintaining any structural assumptions necessary for carrying out simulations of policy changes, given limitations of available data.

In practice, specification testing may begin by starting with a very parsimonious model and relaxing restrictions, or testing successive restrictions placed on an initially flexible model. Classical tests such as the Likelihood Ratio can be used to test the statistical difference between nested models. A sequence of such tests are necessary to try to distinguish between various parsimonious models which are non-nested. Another way to test for the appropriateness of models is to simply examine how policy inferences are affected by additional simplifying restrictions.

The specification search methodology followed is to first estimate a parsimonious non-linear model, a simpler linear model, and a more fully parameterized flexible functional form. These are outlined under the assumption that monetary prices are zero (hence p=w*T), for conformity with the empirical work in the this paper, but out-of-pocket costs are easily accommodated.

(17) $\beta_{0j} + \beta_{1j}X + \beta_{2j}w^*T_j + \beta_{3j}(w^*T_j)^2 + \beta_{4j}w^*T_j{}^*Y$

where a) $\beta_4 = -2\beta_3$

b) $\beta_{ij} = \beta_{ik}$ for i=2,3,4

(18) $\beta_{0j} + \beta_{1j}X + (\beta_{2j}+\beta_{7j})T_j + (\beta_{2j}+\beta_{8j})w + \beta_{5j}Y$

(19) $\beta_{0j} + \beta_{1j}X + \beta_{2j}w^*T_j + \beta_{3j}(w^*T_j)^2 + \beta_{4j}w^*T_j{}^*Y + \beta_{5j}Y + \beta_{7j}T_j + \beta_{8j}w$

If the parameters of interest are relatively stable between these specifications, then no further searching is required. If they differ, however, then it is important to estimate equations which are not overly restrictive, yet remain manageable. Based on the issues discussed in the earlier sections, there are several tests which may be useful in empirically selecting the most appropriate specification. Analyzing several of these jointly may also be required, since joint confidence regions are elliptical rather than the rectangular intersections of individual tests.

A. *Income Specification*

Take (17) and add income specific variables. Further modify this by dropping the P*Y variable. Re-estimate (18), and (19), dropping the choice-specific income variables and in (18) adding $\beta_{4j}P_j*Y$.

B. *Choice-Specific Own-Price Coefficients*

Relax restriction (b) in (17), allowing price coefficients to vary by choice. In (18) and (19), constrain by choice the T coefficients, as well as the T interactions and quadratics.

C. *Choice-Specific Cross-Price Coefficients*

Add cross-price terms to (17), (18), and (19).

D. *Budgeting Parameter λ in Consumption Quadratic*

In (17), relax restriction (a); then impose it in (19).

E. *Travel Time and Opportunity Cost of Time*

In (17), add w and T terms independent of the w*T interaction. In (18) add the w*T interaction, and in (19) experiment with dropping combinations of w,T and w*T.

When these tests have been completed, it can be determined which restrictions appear violated by the data, and which may be reasonably imposed for parsimony. Before using the resulting specification in a particular context, it should then be verified that it can be justified by the economic theory proposed in this paper.

5.4 Illustrating Model Choice with Cote d'Ivoire Data

Results of several of the specification tests were discussed in Section 3. Here, the flexible model of equation (19) is estimated, and then the effects of imposing each restriction type is tested. Regression 3.1 shows the results of estimating the basic flexible model #3, and it is seen from Table 2 that the resulting elasticities differ somewhat from those of the linear and parsimonious specifications. Both the hospital and clinic travel time elasticities of demand are around -0.1, but only the clinic one is significantly different from zero.

The first restriction tested is to in turn drop the linear income variables (regression 4.3), and then the price*income interaction (regression 4.4). As was found in the earlier tests, these specifications of the income variable make little difference. This is an important "non-finding," given the theoretical controversies over the income specification. Based on these data, it suggests that Gertler and van der Gaag (1990) appropriately restricted income not to have alternative-specific coefficients in their model. At the same time, it indicates that the many linear models estimated may not have been incorrect either in omitting the quadratic consumption term (which yields the interaction between price and consumption).

Next, the alternative-specific price coefficients are constrained to equality, to test for the importance of the consumption*health interaction in the utility function (regression 5.4). This leads to a quadrupling of the hospital elasticity, which confirms the importance found in Section 3 of relaxing this restriction. The data indicate that the marginal disutility of a change in the hospital price when a hospital is chosen is different from that of a change in the clinic price when a clinic is chosen.

In contrast, little effect is shown on the elasticities or the likelihood when cross-prices are added to the flexible model (regression 6.3). This differs from the Section 3 findings with the linear and parsimonious models, which implies that the non-linear terms provide an alternative way to explain price variation.

The affect of imposing the $\lambda=1$ restriction on the budgeting period also has a mixed effect. In the flexible model the LR test strongly rejects it (regression 7.2), and although the hospital elasticity is unaffected, it causes a doubling of the clinic elasticity.

Finally, when the separate time and wage variables are dropped from the flexible specification, there is very little effect (regression 8.4). LR tests do not reject constraining these parameters, and elasticities are virtually unchanged. The inclusion of these variables did have a large impact on the parsimonious model, however, indicating their complex effect on health care decisions.

5.5: Which Specification is Preferred?

The results of the previous section suggest that the additional terms in the flexible model substantially improve the explanatory power of either of the more restrictive models, and thus may prove necessary for proper policy inference. Travel time elasticities are an important focus of many health care demand studies, and they were shown here to be sensitive to specification. Furthermore, the sensitivity found here is not only important statistically, but also economically. In moving from the parsimonious non-linear specification to the flexible one, it was found that hospital elasticities decreased from -.46 to -.12. This was chiefly due to relaxing the equality constraint on the hospital and clinic coefficients. A large literature has been devoted to determining whether or not such elasticities are different from zero. The finding that hospital elasticities are not large carries very different policy implications than if they are considered large and more important than clinic ones.

Furthermore, the elasticities for the flexible model [**3.3**] are very low, around -.10, in contrast to the Gertler and van der Gaag (1990) results (elasticities also differ because they report arc elasticities). Does this mean that demand is actually very inelastic in Cote d'Ivoire, as was found in many earlier studies such as Akin (1985) in the Philippines? The answer is no, but the exact cause may require further research. Table 9 presents results estimated only for the lowest quartile of the income distribution[7]. For this sub-sample, the flexible model now yields hospital and clinic own-time elasticities of -1.52 and -.61, respectively. When instead these elasticities are simulated for the lowest income quartile, but based on the estimates pooled across income quartiles [**3.1**], they are -.18 and -.18 (Table 2, row 10).

Even the flexible model advocated in this paper is not sufficient to capture the extreme non-linearities in price effects across income groups. One potential solution is to add higher order price*income interaction terms, through including higher order consumption terms in the utility function of the structural model. However, it may still prove difficult to not reject pooling across income groups. Instead, when analysis is desired for differences across such groups, estimation may be stratified

[7] Stratifying the sample on income requires the income variable to be uncorrelated with the error term. That assumption has been maintained throughout the analysis, as income is treated as exogenous in the estimation.

on that grouping.

SECTION 6: CONCLUSION

The literature on the demand for health care is maturing. Gertler et al. (1987) suggested important theoretical innovations to the behavioral models behind the specification and interpretation of results. This paper enriches that behavioral framework, showing how more flexible models can and often should be used for structural demand estimation.

In the Cote d'Ivoire data analyzed in this paper, the choice between disputed specifications of income variables (which are shown to both have structural interpretations) do not seem to significantly affect price elasticities. A much bigger impact is found by instead stratifying the estimation on income quartiles. Furthermore, non-linear price terms and independent time and wage variables do appear to significantly enhance predictive power. Most importantly, allowing facility characteristics such as prices to have separate alternative-specific coefficients (i.e. relaxing the McFadden conditional logit restrictions) can yield large improvements in explaining demand, and significantly affect policy inference. The results here indicate that sensitivity analyses of the type illustrated in Section 4 should be routinely carried out in other studies of health care demand.

The flexible model introduced in Section 2 both allows for the utility of health and consumption to depend on each other, and also allows for dynamic expectations of future health and consumption to affect demand. These innovations provide a rigorous foundation for the flexible alternative specifications which are explored in this paper. Parsimony and adherence to a structural model which reflects rational choice are important. These can be accommodated, however, along with the third important goal of utilizing a specification flexible enough to not be rejected by the data.

Appendix: **Comparative Static Predictions of the Flexible Model**

Because many of the important policy variables enter this model through multiple pathways, it is worth explicitly examining their expected signs. To be precise, marginal effects are derived from the exact indirect conditional utility function specified here, rather than using implicit functions. However, because only discrete bundles are assumed available, the usual calculus maximization of the utility function to derive the demand equations is not applicable. Instead, let demand D_j represent the probability of choosing input bundle j from the exhaustive set J of choices (one and only one of which must be chosen). Thus

$$D_j = \text{Prob}(U_j > U_k \text{ for all } k \in J)$$

Represent the observable portion of utility as $Z_j'\beta_j$, giving:

$$D_j = \text{Prob}(Z_j'\beta_j - Z_k'\beta_k > \epsilon_k - \epsilon_j)$$

By assuming the ϵ are distributed iid type I extreme value, a particular closed form expressions can be given for the marginal effects, as a function of the estimable parameters. If alternatively the normal distribution were chosen this would not significantly change the equations given; the assumption here is made simply for ease of presentation. This assumption results in the multinomial logit statistical model:

$$D_j = \exp(Z_j'\beta_j)/[\exp(Z_j'\beta_j) + \exp(Z_k'\beta_k)]$$

The comparative statics of interest then are simply: dD_j/dZ.

In order to sign the marginal effects, some reasonable assumptions must be made on the structural parameters:

$\alpha_1>0$, $\alpha_2<0$, $\alpha_3>0$, $\alpha_4>0$, $\alpha_5>0$, $\alpha_6>0$, $\alpha_7<>0$

$Q>0$, $Q_j^c>0$, $Q_j^b>0$, $Q_j^x<>0$, $Q_j^T<0$, $\lambda>0$, $\delta>0$, $E[q]>0$, $E[A]>0$

For ease of presentation, also assume for this section that there are only 2 choices, j and k, thus $D_j+D_k=1$. Furthermore, assume that j is higher priced ($p_j>p_k$) and yields higher health benefits ($Q_j>Q_k$).

By themselves, these assumptions imply certain expectations on the individual signs of the estimated parameters. It can be inferred that $\beta_2<0$, $(\beta_{5j}-\beta_{5k})>0$, $\beta_6<0$, and $\beta_7<0$. If it is further assumed that $\alpha_7<0$, then unambiguously $\beta_3<0$ for the price quadratic, and $\beta_4>0$ on the price*income interaction. Otherwise these signs are probable, but require more complex restrictions on α_7, as discussed below.

Next, the marginal effects on demand are derived for particular variables of interest:

Prices. If health is a normal good, then ceteris paribus demand for health will decrease as the price of producing health increases. Thus as the price of a health input j increases, demand for the input j would also decrease. The cross-price effects on demand for j when the price of k changes, however, will as usual be a priori ambiguous. These price effects may differ by alternative, through the consumption*health interaction in the utility function, when α_6 or α_6 differ from zero.

$$dD_j/dp_j \quad = D_jD_k[\beta_{2j} + 2\beta_{3j}{*}p_j + \beta_{4j}{*}Y - \beta_{6k}]$$

$$= D_jD_k\{[-(\alpha_1+\alpha_6 Q_j^c)] + [-2(\lambda Y-P_j)(\alpha_2+\alpha_7 Q_j^c)] + [-\alpha_3(E[q_j^j-q_k^j]]\}$$

The first term inside the brackets is assumed negative, the second will be negative if $\alpha_7<0$, and the third negative if visits to provider j generate more follow-up visits to facility j than do visits to k. The assumption that health is a normal good would be incorrect if α_2, α_6, and/or $E[q_j^j-q_k^j]$ were sufficiently negative.

$$dD_j/dp_k \quad = D_jD_k[\beta_{6j} - (\beta_{2k} + 2\beta_{3k}{*}p_k + \beta_{4k}{*}Y)$$

$$= D_jD_k\{[(\alpha_1+\alpha_6Q_k^c)] + [2(\lambda Y-P_k)(\alpha_2+\alpha_7Q_k^c)] + [\alpha_5E[q_k^k-q_j^k]]\}$$

The first term of this cross-effect is assumed positive, and again the second and third cannot be signed a priori. Note that the model could easily be re-written for three choices, and marginal effects derived for example for hospital demand, when prices are raised simultaneously for both hospital and clinic care, holding constant the cost of self-care.

Health Facility User Fees. The marginal effects for user fees are almost exactly the same as for the general "price" variable discussed above. The sole difference is that "F" should be substituted for "p" in the second term of the equations.

Travel Cost. Again, travel cost effects will be similar to those of price. Simply substitute "δ*T*w" for "p", and multiply by δ.

Travel Times. Travel times are slightly more complicated, as they enter demand both through price and through health production. Let dD_j/dp^T denote the price marginal effect's formula with "δwT" substituted for "p" in the second term. Then:

$$dD_j/dT_j = (dD_j/dp^T)\delta w + D_jD_k\beta_{7j}$$

Higher travel times are thus predicted to decrease demand, assuming again that health is a normal good, and $\beta_{7j}<0$. Note that this effect may differ by alternative, if the disutility of traveling is altered following pain relief from a care visit, for example.

Income. Permanent income is modeled to affect health input choices via the consumption terms, yielding:

$$dD_j/dY \quad = D_jD_k[\beta_{4j}p_j - \beta_{4k}p_k + \beta_{5j} - \beta_{5k}]$$

$$= D_j D_k\{[-2\alpha_2\lambda(p_j-p_k)] + [\alpha_6\lambda(Q_j^c-Q_k^c)] + [-2\alpha_7\lambda(p_jQ_j^c-p_kQ_k^c)]\}$$

The first two terms in brackets are assumed positive. The third term could be negative if $\alpha_7>0$, thus tempering the income effect. If health is a normal good as assumed, however, then the overall sign will of course be positive.

Notice that income does not affect choices through the linear consumption term (α_1 does not enter the equation), since it is constant across alternatives, and thus does not affect the difference in utility between them. This was highlighted by Gertler et al. (1987), who instead included the quadratic in consumption, which allows income to affect choice since it is now interacted with price, which varies across alternatives. However, income will also affect choice in this model through the consumption interaction with health, which allows a non-constant marginal rate of substitution between income and health. This implies that even if the quadratic consumption term were not included ($\alpha_2=0$), income could affect choice. Separate alternative-specific income coefficients may thus logically be estimated in this model, in contrast to the Gertler et al. (1987, 1990) models. Yet this model still meets their condition that if the price and health improvement in the two options were equal, then a person would be indifferent between the choices.

Unearned income. A distinction may be made between the marginal effects of earned and unearned income. In this model, the permanent income effect dD_j/dY just derived above is exactly the same as the marginal effect of unearned income. Earned income is more complicated however, and instead the effect of a change in wages is given next.

Wages. The marginal effect of wages cannot be predicted a priori. This is because higher wages increase the opportunity cost of time spent in seeking care, but they also increase the cost of remaining sick, and have an income effect through the consumption term. This can be written as the sum of the effect through p_j, the effect through p_k, the income effect, and a new effect ($D_j D_k(\beta_{8j} - \beta_{8k})$) reflecting the opportunity cost of being sick:

$$dD_j/dw = (dD_j/dp_j)\,\delta T_j + (dD_j/dp_k)\,\delta T_k + (dD_j/dY)(dY/dw) + D_j D_k \alpha_5 [A_k - A_j]$$

The first term is negative, and the second of ambiguous sign. The third is positive, although often it is difficult to measure dY/dw, thus empirically the total effect of wages is rarely estimated. The final term is positive in this model, but would be ambiguous in more complex (but realistic) models where absenteeism depends on the wage.

Income,Price Cross-Effect. How the effect of prices varies with income is of interest. This can be seen through the derivative of the own-price elasticity of demand for j (E_j^j) with respect to income:

$$dE_j^j/dY = P_j[D_k \beta_{4j} + (1/D_j D_k)(dD_j/dp_j)(dD_k/dY)]$$

Again assuming that health is a normal good, this effect will be positive, as also found by Gertler and van der Gaag (1990). In other words, richer people are less sensitive to price changes.

X variables. The effects of education, age, gender, etc. may also not be possible to sign a priori.

$$dD_j/dX = D_j D_k[\beta_{1j} - \beta_{1k}]$$
$$= D_j D_k \alpha_4 (Q_j^x - Q_k^x)$$

For example, education may make a person more likely to understand and benefit from a doctor's orders, but at the same time it could also increase a person's productivity in taking care of themselves at home without seeing a doctor.

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Table 1: Descriptive Statistics for Sick Population

Variable	Mean	Standard Deviation
Probability visit Hospital (last 4 weeks)	.14	.35
Probability visit Clinic (last 4 weeks)	.23	.42
Travel Time: Hospital (hours, round trip)	1.86	1.77
Travel Time: Clinic	1.12	1.24
Wage (hourly, 1985 CFA)[1,2]	66.3	25.0
Income (monthly, 1985 CFA)[3]	21,845	18,229
Age[2]	44.3	17.2
Male	.42	.49
Education (years)	.87	2.23

Sample Size = 1359

[1]Community daily agricultural wage by gender, divided by eight hours.

[2]Divided by 100 for estimation.

[3]Permanent income is proxied by total household consumption, normalized by number of adults in household. Divided by 10,000 for estimation.

Table 2: Time-Price (own) Elasticities[1] of Demand

(leftmost column gives Table # and column of regression results)

Regression[2]	Hospital	Clinic	Log-Likelihood*(-1)
3.1	-.46	-.24	1199.5
3.2	-.11	-.28	1184.6
3.3	-.12	-.11	1153.4
4.1	-.50	-.24	1191.5
4.2	-.03	-.28	1179.1
4.3	-.09	-.11	1156.2
4.4	-.14	-.11	1156.7
5.1	-.35	-.28	1194.4
5.2	-.19	-.25	1180.0
5.3	-.33	-.19	1196.3
5.4	-.47	-.24	1189.0
6.1	-.23	-.24	1174.5
6.2	-.17	-.21	1176.6
6.3	-.10	-.13	1153.0
7.1	-.40	-.23	1193.0
7.2	-.12	-.23	1163.7
7.3	-.10	-.10	1157.4
8.1	-.15	-.29	1187.6
8.2	-.47	-.24	1199.5
8.3	-.27	-.30	1180.4
8.4	-.13	-.11	1154.5
9.1	-.43	-.24	257.9
9.2	-1.05	-.37	247.0
9.3	-1.52	-.61	235.1
10.1[2]	-.43	-.27	
10.2[2]	-.12	-.36	
10.3[2]	-.18	-.18	

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[1]Calculated by simulating predicted probabilities after 1% Travel Time increase, and averaging over individuals.

[2]Calculated as the average change in predicted probabilities only for the lowest income quartile, using regressions 3.1-3.3.

Table 3: **Nested[1] Logit results from Section 4.1 Specifications[2]**

	Parsimonious Non-linear	Linear	Flexible
Time Hosp_h[3]		-.07 (1.06)	.16 (1.44)
Time Clin_c		-.55 (4.72)	-.01 (.05)
TimeH*wage_h[4]	-.40 (4.35)		-.51 (1.24)
TimeC*wage_c	-.40 (4.35)		-1.89 (3.84)
Age_h	-2.09 (4.60)	-2.22 (3.59)	-2.00 (3.74)
Age_c	-1.47 (3.72)	-1.37 (2.87)	-1.68 (3.74)
Male_h	.23 (1.56)	.35 (1.69)	.26 (1.49)
Male_c	.01 (.05)	-.09 (.56)	-.08 (.52)
Education_h	-.01 (.43)	.00 (.00)	-.00 (.10)
Education_c	-.02 (.57)	-.05 (1.25)	-.07 (1.87)
Wage_h		-.73 (1.77)	.25 (.51)
Wage_c		-.24 (.79)	-.09 (.26)
Income_h		.14 (3.31)	.06 (.82)
Income_c		.06 (1.50)	.12 (2.42)
(Wage*TimeH)^2[5]	-.005 (.39)		-.04 (.55)
(Wage*TimeC)^2	-.005 (.39)		.58 (5.14)
Wage*TimeH*Income[6]	-.005 (.39)		-.04 (1.25)
Wage*TimeC*Income	-.005 (.39)		.08 (1.77)
Intercept_h	.19 (.88)	-.55 (1.11)	-.79 (1.77)
Intercept_c	.13 (.63)	.15 (.42)	.42 (1.27)
Inclusive value[7]	.53 (2.94)	1.18 (.51)	.90 (.48)
log-Likelihood	-1199.5	-1184.6	-1153.36

Notes for Tables 3-9:

[1]All models have been estimated with hospital and clinic being nested separately from self-care.

[2]Absolute values of t-statistics in parentheses.

[3]_h, _c suffixes indicate the coefficient measures the effect of the variable on the hospital, and clinic options, respectively.

[4]This wage*time interaction is the hospital time-price term, divided by 100 for estimation.

[5]This squared time-price term is divided by 10,000 for estimation.

[6]This price*income interaction is multiplied by (-2) to correctly impose the equality restriction with the quadratic price coefficient. Divided by 10^6 for estimation.

[7]Coefficient on the inclusive value term of the hospital-clinic nest; t-test is for null hypothesis that coefficient equals one.

Table 4: Testing Income Specifications

	Income-Specific Variables with Pars	Price*Income Interaction with Linear	Drop Income from Flex	Drop Price*Y Interaction from Flex
Time Hosp_h		-.23	.16	.15
		(2.21)	(1.34)	(1.36)
Time Clin_c		-.34	-.02	.03
		(2.37)	(.12)	(.18)
TimeH*wage_h	-.34		-.55	-.22
	(4.15)		(1.31)	(.64)
TimeC*wage_c	-.34		-2.24	-2.23
	(4.15)		(4.64)	(4.96)
Age_h	-1.96	-2.16	-2.06	-1.99
	(4.40)	(3.30)	(3.70)	(3.84)
Age_c	-1.46	-1.40	-1.69	-1.65
	(3.73)	(2.81)	(3.64)	(3.73)
Male_h	.19	.38	.29	.24
	(1.36)	(1.72)	(1.59)	(1.40)
Male_c	.01	-.11	-.10	-.08
	(.05)	(.62)	(.63)	(.50)
Education_h	-0.02	.01	-.00	-.00
	(0.59)	(.21)	(.02)	(.13)
Education_c	-0.03	-.05	-.06	-.06
	(.83)	(1.36)	(1.73)	(1.73)
Wage_h		-.74	.21	.25
		(1.66)	(.39)	(.54)
Wage_c		-.22	-.01	-.03
		(.69)	(.02)	(.10)
Income_h	.16	.03		.13
	(3.83)	(.38)		(3.27)
Income_c	.11	.12		.07
	(3.01)	(2.31)		(1.82)
(Wage*TimeH)^2	.02		-.05	-.06
	(1.90)		(.61)	(.94)
(Wage*TimeC)^2	.02		.63	.59
	(1.90)		(5.70)	(5.28)
Wage*TimeH*Income	.02	.09	-.06	
	(1.90)	(1.87)	(2.88)	
Wage*TimeC*Income	.02	-.14	.02	
	(1.90)	(1.95)	(.69)	
Intercept_h	-0.13	-.55	-.76	-.92
	(.57)	(1.00)	(1.64)	(2.17)
Intercept_c	-0.08	-.03	.64	.48
	(.37)	(.07)	(1.94)	(1.47)
Inclusive value	.48	1.35	1.00	.83
	(-3.68)	(.86)	(-.01)	(-.86)
log-Likelihood	-1191.5	-1179.1	-1156.2	-1156.73

Table 5: Testing Choice-Specific Price Coefficients

	Allow Linear Alt.-Spec Price Coeffs with Pars	Allow all Price Vars with Alt-Spec Coeffics; Pars	Constrain Travel Coeffs Across Alts with Linear	Constrain Travel Across Alts with Flex
Time Hosp_h			-.29 (5.03)	.09 (1.45)
Time Clin_c			-.29 (5.03)	.09 (1.45)
TimeH*wage_h	-.30 (4.13)	-.29 (2.95)		-.71 (3.10)
TimeC*wage_c	-.58 (4.20)	-.56 (4.25)		-.71 (3.10)
Age_h	-2.03 (4.43)	-2.07 (3.92)	-2.39 (3.74)	-1.92 (4.26)
Age_c	-1.52 (3.72)	-1.66 (3.82)	-1.21 (2.60)	-1.48 (3.78)
Male_h	.21 (1.40)	.27 (1.57)	.37 (1.74)	.18 (1.23)
Male_c	.02 (.13)	-.00 (.01)	-.11 (.70)	-.01 (.04)
Education_h	-.01 (.31)	-.01 (.16)	-.02 (.39)	-.02 (.59)
Education_c	-.02 (.78)	-.04 (1.10)	-.03 (.84)	-.03 (.86)
Wage_h			-.93 (1.96)	.33 (.97)
Wage_c			-.03 (.10)	.30 (1.12)
Income_h			.13 (3.15)	.11 (2.50)
Income_c			.07 (1.80)	.08 (1.91)
(Wage*TimeH)^2	-.01 (1.00)	-.04 (1.36)		.06 (2.08)
(Wage*TimeC)^2	-.01 (1.00)	.12 (2.01)		.06 (2.08)
Wage*TimeH*Income	-.01 (1.00)	-.04 (1.36)		-.00 (.17)
Wage*TimeC*Income	-.01 (1.00)	.12 (2.01)		-.00 (.17)
Intercept_h	.02 (.06)	-.36 (.74)	.09 (.23)	-.21 (.68)
Intercept_c	.21 (1.03)	.32 (1.35)	-.27 (.71)	-.16 (.60)
Inclusive value	.58 (-2.43)	.84 (-.43)	1.10 (.26)	.46 (-3.12)
log-Likelihood	-1194.4	-1180.0	-1196.3	-1189.0

Table 6: Testing Cross-Price Restrictions

	Cross-Prices with Pars	Cross-Prices with Linear	Cross-Prices with Flex
Time Hosp_h		-.38 (1.39)	.16 (1.66)
Time Hosp_c		1.78 (1.39)	.01 (.13)
Time Clin_h		1.99 (2.78)	-.11 (.99)
Time Clin_c		-2.23 (4.09)	.00 (.01)
TimeH*wage_h	-.86 (2.46)		-.42 (1.20)
TimeH*wage_c	.28 (2.30)		
TimeC*wage_h	1.13 (2.35)		
TimeC*wage_c	-1.17 (3.76)		-1.72 (3.26)
Age_h	-2.63 (2.61)	-4.00 (2.30)	-1.91 (3.92)
Age_c	-1.34 (1.96)	-.32 (.27)	-1.73 (4.04)
Male_h	.46 (1.45)	1.35 (2.13)	.21 (1.30)
Male_c	-.15 (.63)	-.78 (1.76)	-.04 (.26)
Education_h	.04 (.52)	-.02 (.15)	-.01 (.31)
Education_c	-.08 (1.23)	-.04 (.36)	-.06 (1.79)
Wage_h		-.00 (.00)	.11 (.24)
Wage_c		-63 (.76)	-.11 (.33)
Income_h		.21 (1.88)	.07 (1.14)
Income_c		.01 (.15)	.12 (2.63)
(Wage*TimeH)^2	-.16 (3.49)		-.03 (.54)
(Wage*TimeC)^2	.28 (3.51)		.51 (3.57)
Wage*TimeH*Income	-.16 (3.49)		-.03 (.85)
Wage*TimeC*Income	.28 (3.51)		.07 (1.69)
Intercept_h	-2.69 (2.41)	-10.03 (2.14)	-.48 (.92)
Intercept_c	-.55 (1.00)	-2.53 (1.42)	.46 (1.40)
Inclusive value	2.93 (1.98)	9.20 (2.02)	.69 (-1.16)
log-Likelihood	-1174.5	-1176.6	-1153.0

Table 7: Testing Budgeting Assumptions in the Price Quadratic

	Relax λ=1 with Pars	Impose λ=1 with Flex	Relax both λ=1 *and* alt-spec price constraints; Pars
Time Hosp_h		.16 (1.39)	
Time Clin_c		-.41 (1.77)	
TimeH*wage_h	-.93 (4.45)	-.52 (2.30)	-.18 (.58)
TimeC*wage_c	-.93 (4.45)	.10 (.35)	-2.31 (6.59)
Age_h	-2.16 (4.33)	-2.08 (3.62)	-2.08 (3.75)
Age_c	-1.44 (3.44)	-1.60 (3.46)	-1.69 (3.65)
Male_h	.27 (1.66)	.31 (1.60)	.27 (1.54)
Male_c	-.01 (.11)	-.06 (.40)	-.10 (.64)
Education_h	-.02 (.50)	-.00 (.07)	-.00 (.09)
Education_c	-.03 (.83)	-.06 (1.67)	-.06 (1.74)
Wage_h		.19 (.35)	
Wage_c		-.35 (.94)	
Income_h		.05 (.75)	
Income_c		.20 (4.16)	
(Wage*TimeH)^2	.09 (2.75)	-.05 (1.14)	-.08 (1.01)
(Wage*TimeC)^2	.09 (2.75)	.21 (3.42)	.64 (6.10)
Wage*TimeH*Income	-.04 (2.44)	-.05 (1.14)	-.06 (2.89)
Wage*TimeC*Income	-.04 (2.44)	.21 (3.42)	.02 (.70)
Intercept_h	.23 (.91)	-.85 (1.83)	-.63 (1.60)
Intercept_c	.17 (.80)	.17 (.51)	.64 (2.63)
Inclusive value	.71 (-1.31)	1.01 (.03)	1.00 (.01)
log-Likelihood	-1193.0	-1163.7	-1157.4

Table 8: Testing Travel Time and Wage Assumptions

	Alt-Spec Travel Time with Pars	Constrained Travel Time with Pars	Time*wage Interaction with Linear	Drop Separate Time, Wage from Flex
Time Hosp_h	.06 (.74)	.00 (.06)	.17 (1.93)	
Time Clin_c	-.36 (2.17)	.00 (.06)	-.40 (1.65)	
TimeH*wage_h	-.29 (2.11)	-.40 (3.67)	-.53 (3.33)	-.13 (.39)
TimeC*wage_c	-.29 (2.11)	-.40 (3.67)	-.02 (.07)	-1.93 (5.16)
Age_h	-2.18 (3.92)	-2.08 (4.43)	-1.97 (4.01)	-2.03 (3.77)
Age_c	-1.45 (3.22)	-1.47 (3.72)	-1.47 (3.55)	-1.67 (3.70)
Male_h	.30 (1.63)	.22 (1.53)	.23 (1.40)	.25 (1.45)
Male_c	-.06 (.39)	.01 (.06)	-.03 (.18)	-.09 (.60)
Education_h	-.00 (.05)	-.01 (.42)	-.01 (.35)	-.01 (.14)
Education_c	-.04 (1.14)	-.02 (.56)	-.03 (1.08)	-.07 (1.91)
Wage_h			.44 (1.10)	
Wage_c			-.21 (.60)	
Income_h			.12 (3.30)	.06 (.87)
Income_c			.07 (2.02)	.12 (2.40)
(Wage*TimeH)^2	-.02 (1.52)	-.01 (.38)		-.07 (.99)
(Wage*TimeC)^2	-.02 (1.52)	-.01 (.38)		.59 (5.50)
Wage*TimeH*Income	-.02 (1.52)	-.01 (.38)		-.04 (1.16)
Wage*TimeC*Income	-.02 (1.52)	-.01 (.38)		.08 (1.80)
Intercept_h	-.47 (1.01)	.19 (.89)	-.69 (1.83)	-.68 (1.72)
Intercept_c	.19 (.78)	.13 (.64)	.22 (.72)	.37 (1.41)
Inclusive value	.96 (-.12)	.52 (-2.32)	.67 (-1.33)	.92 (-.40)
log-Likelihood	-1187.6	-1199.5	-1180.4	-1154.5

Table 9: Low-Income Quartile: Three Basic Specifications

	Low-Income Parsimonious	Low-Income Linear	Low-Income Flexible
Time Hosp_h		-.39	-.61
		(2.40)	(2.16)
Time Clin_c		-.27	-.29
		(2.45)	(1.73)
TimeH*wage_h	-.42		-1.21
	(1.78)		(1.50)
TimeC*wage_c	-.42		-1.56
	(1.78)		(1.99)
Age_h	-1.79	-1.56	-1.35
	(1.63)	(1.63)	(1.68)
Age_c	-.86	-.92	-1.10
	(1.04)	(1.14)	(1.39)
Male_h	.74	.69	.49
	(1.89)	(2.02)	(1.74)
Male_c	.34	.37	.37
	(1.24)	(1.33)	(1.37)
Education_h	-.07	-.08	-.09
	(.68)	(.93)	(1.09)
Education_c	-.03	-.05	-.08
	(.31)	(.68)	(.94)
Wage_h		-.71	-1.37
		(1.06)	(1.73)
Wage_c		-.35	-.58
		(.64)	(.94)
Income_h		2.65	.47
		(3.00)	(.58)
Income_c		1.56	.65
		(2.60)	(.89)
(Wage*TimeH)^2	.01		-.04
	(.22)		(.71)
(Wage*TimeC)^2	.01		.17
	(.22)		(1.69)
Wage*TimeH*Income	.01		-1.21
	(.22)		(2.17)
Wage*TimeC*Income	.01		-.87
	(.22)		(2.15)
Intercept_h	-.64	-1.82	.35
	(1.10)	(2.04)	(.35)
Intercept_c	-.47	-1.24	-.24
	(1.08)	(1.82)	(.29)
Inclusive value	.55	.35	.09
	(-1.05)	(-2.76)	(-17.55)
log-Likelihood	-257.9	-247.0	-235.1

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