DISCUSSION PAPERS IN ECONOMICS

Working Paper No. 98-25

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June 1998

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June 8, 1998
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Abstract

A step-income-effects logit model is used to estimate provider choice from six types by malaria patients in rural Nepal. Patient characteristics that influence choice include travel costs, income category, household size, gender, and type and severity of malaria. Significant provider characteristics include wait time for treatment and wait time for laboratory results. The expected value of each patient's household compensating variation, $E[CV]$, is estimated for increasing the number of providers, providing more sites with blood testing capabilities, and initiating drug charges with and without improvements in health care. The $E[CV]$s vary significantly across households and allow one to assess how much different households would benefit or lose under different government proposals.

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[1]We thank Anna Alberini, Charles de Bartolomé, Bill Breffle, Michael Greenwood, and Bill Riebsame for help and comments.

1. Introduction

This paper estimates the compensating variations, *CV*s,, the households of malaria patients would associate with different proposals for improving malaria treatment in rural Nepal. These estimated *CV*s measure, in money, the extent to which different households would gain or lose under different proposals.[2] Choice of provider type is modeled and estimated using a discrete-choice random utility model, specifically a logit model that incorporates provider and patient characteristics, and that allows individuals in different income categories to have different marginal utilities of income.

The government of Nepal has proposed or initiated a number of programs to expand and improve primary care services in rural areas. These include providing each village with a health care volunteer, providing each group of villages with a health care facility, and providing more health care facilities with blood testing capabilities. The government is also considering requiring patients to pay for drugs; public providers currently provide them for free.

Sixty percent of Nepal's population is considered to be at risk of contracting malaria, but in any given year only a small percent of the at-risk population contracts malaria. Between 1990 and 1993 the number of confirmed cases varied between 16,000 and 29,000 (Department of Health Services 1994). Individuals can receive treatment from a number of different government providers or private providers, including faith healers, and choice varies significantly across individuals and districts. An important issue is what patient and provider characteristics determine the choice of treatment. The government's malaria control program is its oldest and most widely available rural health care program, but there is little information on how patients choose between public and private providers, how patients choose among the different types of government providers, and the benefits the patients receive from the availability of different treatment options.

The focus on malaria allows us concentrate on the determinants of choice that are specific to that illness. Three other studies of provider choice have modeled a single illness or service: de Bartolomé and Vosti (1995) for malaria in Brazil, Schwartz *et al.* (1988) for infant delivery in the Philippines, and Akin *et al.* (1986b) who estimate

[2]A household's compensating variation for a proposal is the amount of money that has to be added to or subtracted from the household's income when the health care proposal is implemented to make the maximum utility of the household with the proposal and income compensation equal to its maximum utility in the current state. Denote its expected value $E[CV]$.

separate models for a number of different aspects of infant treatment. In contrast, Dor *et al.* (1987), Gertler *et al.* (1987), Mwabu *et al.* (1993), Ellis *et al.* (1994), and Akin *et al.* (1995) model either outpatient or inpatient services broadly. Choosing a specific illness makes it easier to identify the specific determinants of choice.

Incorporating provider characteristics is essential if the intent is to value changes in provider characteristics. Studies that incorporate provider characteristics include Schwartz *et al.* (1988), Litvack and Bodart (1993), Mwabu *et al.* (1993), Ellis *et al.* (1994) and Akin *et al.* (1995).[3] We find a number of provider characteristics to be important determinants of choice.

The patient's gender and severity of malaria are investigated as determinants of provider choice. The severity of the illness is determined by the species and density of malaria parasites infecting the patient. There are two species of malaria parasites in Nepal: *Plasmodium vivax* (PV) and *Plasmodium falciparum* (PF). PV is the most common form of malaria and typically does not result in complications. If PF is untreated it can lead to complications such as brain and kidney damage and can be fatal. The incidence of PF varies significantly across districts in Nepal. The intensity of malaria's symptoms (shivering, fever, and headache) is generally positively correlated with the density of parasites in the blood.

Choices with respect to treatment for tropical diseases can differ by gender for economic, social, and cultural reasons, see Rathgeber and Vlassoff (1993). Akin *et al.* (1986a and 1986b), Paul (1992), Ellis *et al.* (1994), Akin *et al.* (1995), and Ching (1995) find gender a significant determinant of choice in developing countries.[4] In Nepal, in particular, it is likely that the impact of malaria programs on household welfare will depend on the patient's gender. Research and personal experience suggest that in Nepal the family considers the welfare of females to be less important than that of males:[5]

> Nepal is one of the few countries in the world where life expectancy of females is less than males. ... In Nepal, almost every indicator, be it female literacy, female life expectancy, female infant mortality, female under-five mortality, maternal mortality, maternal morbidity, or rate of utilization of health care services by

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[3]Studies that use only provider-specific dummies to represent quality of care (Akin *et al.* 1986a and 1986b, Dor *et al.* 1987, Gertler *et al.* 1987, and Ching 1995) preclude the researcher from analyzing the welfare effects of changes in quality.

[4]In contrast, Mwabu *et al*. (1993) and de Bartolomé and Vosti (1995) find it insignificant.

[5]See Bennett (1983), Allen (1990), and Ali (1991) for social and cultural insights into the status of women in Nepal.

females, shows *a fundamental bias and inequity* in favor of men (Ali 1991).

Another important issue is how malaria policies that include additional user fees would affect the poor, both in terms of use rates and welfare. Theory indicates that the effects will depend on the magnitude of the fee increase and the extent to which the quality and level of treatment increase, and this is what the evidence to date indicates.[6] To assess the impact by income group, most studies have estimated only the impact of a proposal on the choice probabilities.[7] However, how use rates of the poor will change when policies change does not identify the welfare impacts on the poor. We use estimated *CV*s, along with changes in use rates, to assess the impacts of different proposals on the poor.

It is difficult to incorporate income effects into discrete choice models in a manner that is both utility-theoretic and that lends itself to the easy derivation of exact compensating or equivalent variations. Since a *CV* is a money measure of a utility change, it is critical that the estimated model be consistent with utility maximizing behavior.

Utility maximization requires that the conditional indirect utility function for each provider alternative be a continuous and non-declining function of residual income (income remaining to spend on the numeraire after paying for the services of that provider). However, a number of the discrete choice models of provider choice do not impose the budget constraint. Instead, they model income separately from cost of services by including income as a variable that determines the "predisposition" of a patient towards alternative providers. See, for example, Akin *et al.* (1986a and b), Schwartz *et al.* (1988), and Bolduc *et al.* (1996). This modeling method is not utility theoretic and, in addition, assumes constant cost effects across all income groups, making the model inappropriate for both evaluating regressiveness and calculating compensating variations. Mwabu (1989), Ellis *et al*. (1994), and Akin *et al.* (1995) interact income with the cost of service; this allows cost effects to vary with income levels, but not in a utility-theoretic manner.

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[6] See, for example, Akin *et al.* (1986a and 1995), Gertler *et al.* (1987), Litvack and Bodart (1993), Mwabu and Mwangi (1986), Mwabu *et al.* (1993), and Schwartz *et al.* (1988).

[7]The exceptions are Mwabu and Mwangi (1986) and Gertler *et al.* (1987). Gertler *et al.* (1987) estimate exact $E[CV]$s. Mwabu and Mwangi (1986) approximate them with areas under the choice probability demand curve (a curve that shows a relationship between user fees and choice probabilities).

Simply put, income effects are incorporated in a utility-theoretic manner by allowing the marginal utility of residual income to vary with income.[8] This can be done by allowing the marginal utility of residual income to vary continuously as a function of residual income (*continuous income effects*) or in steps. We chose steps, in part, because the available information on income is sufficient to place households into income categories but not detailed enough to determine income. A step function also simplifies the derivation of $E[CV]$s. This study seems to be the first model of provider choice to assume step-income effects. When marginal utility of residual income is a constant or a step function of residual income, $E[CV]$ has a simple closed-form solution.[9]

The remainder of the paper is organized as follows. Section 2 describes data and the institutional environment. Section 3 develops a step-income-effects model, and Section 4 reports the results of estimation. The estimated compensating variations for a number of health care proposals are reported and discussed in Section 5. Section 5 also discusses the impact of drug charges.

2. Data and Institutional Environment

The data (Mills 1994) was collected in 1984-1985 in eleven village development committees (VDCs) in Dhanusha district and in fifteen VDCs of Nawalparasi district; a VDC is a unit that governs a group of adjacent villages (see Figure 1).[10] Note that the Nawalparasi sample area is on the border with India. These twenty-six

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[8]Many discrete-choice random utility models avoid the problems associated with income data and income as a determinant of choice by assuming the marginal utility of residual income is a constant (*zero income effects*). In this case, choice probabilities and compensating variations are not a function of income. While it is impossible to evaluate the regressiveness of proposals with such models, they have been used to model provider choice, but mostly for provider choice in developed countries. See, for example, Lee and Cohen (1985), Luft *et al.* (1990), and Adams *et al.* (1991).

[9]With step income effects, existence of a closed-form solution for $E[CV]$ requires that the proposal will not shift the household into a different income category. Utility-theoretic models with continuous-income-effects models include Gertler *et al.* (1987), Dor *et al.* (1987), and Ching (1995). With continuous income effects, $E[CV]$ does not have a closed-form solution, and estimation of $E[CV]$ requires repeated draws from the Extreme Value distribution for a logit model, or repeated draws from a Generalized Extreme Value distribution for a nested-logit model. For details, see McFadden (1996), Herriges and Kling (1997) and Morey (1998). Though Gertler *et al.* (1987) estimated a continuous-income-effects model, when calculating the estimated $E[CV]$s they assumed a constant marginal utility of income. Dor *et al.* (1987), and Ching (1995) do not estimate compensating variations.

[10]The survey was funded by the UK Overseas Development Administration (now The Department for International Development).

VDCs were chosen because they had experienced difficulties in controlling malaria, so had significant numbers of cases.

The population consists of the 905 individuals in the twenty-six VDCs confirmed by a blood test to have had malaria in 1984-85.[11] The intent was to interview each of these 905 patients within two weeks of when their malaria was detected. The two-week limit was imposed to insure accurate recall. 695 were successfully interviewed.[12]

The surveyors recorded choice of provider, the cost incurred to visit that provider, severity and type of malaria, and numerous individual and household characteristics. The model was estimated on the choices of the 489 individuals (314 from Dhanusha and 175 from Nawalparasi) for which there was complete data.[13] The survey of patients was supplemented with data on the locations and attributes of providers collected by the second author.

There are six distinct types of malaria treatment providers: four types of government providers and two types of private providers. Public treatment of malaria is coordinated by the Nepal Malaria Eradication Organization (NMEO) and the Department of Health Services (DOHS).[14] NMEO providers comprise malaria

[11]This population effectively includes everyone in the 26 VDCs who had malaria, because malaria workers visit every home once a month to detect and treat malaria, so even if an individual were treated by a provider who does not test blood, the individual would likely be tested by the malaria worker on his next visit. The only exceptions would be individuals who had malaria, were successfully treated with drugs by a private provider, and reported to the malaria worker that they had not had any symptoms of malaria. The population and sample do not include individuals who sought treatment incorrectly thinking they might have malaria.

[12]Detections often came in clumps, which made it impossible for the surveyors to interview all of the 905 patients within the two-week time limit. Data on the household characteristics of the 210 patients not interviewed were collected at a later date. These 210 patients do not significantly differ from the sample in terms of household characteristics (Mills 1994).

[13]In terms of the data available for those dropped from the sample, the sample of 489 patients is representative of the 695 in terms of patient characteristics, costs, and choices.

[14]Activities of the NMEO have now been integrated with the activities of the DOHS; they were separate entities in 1985.

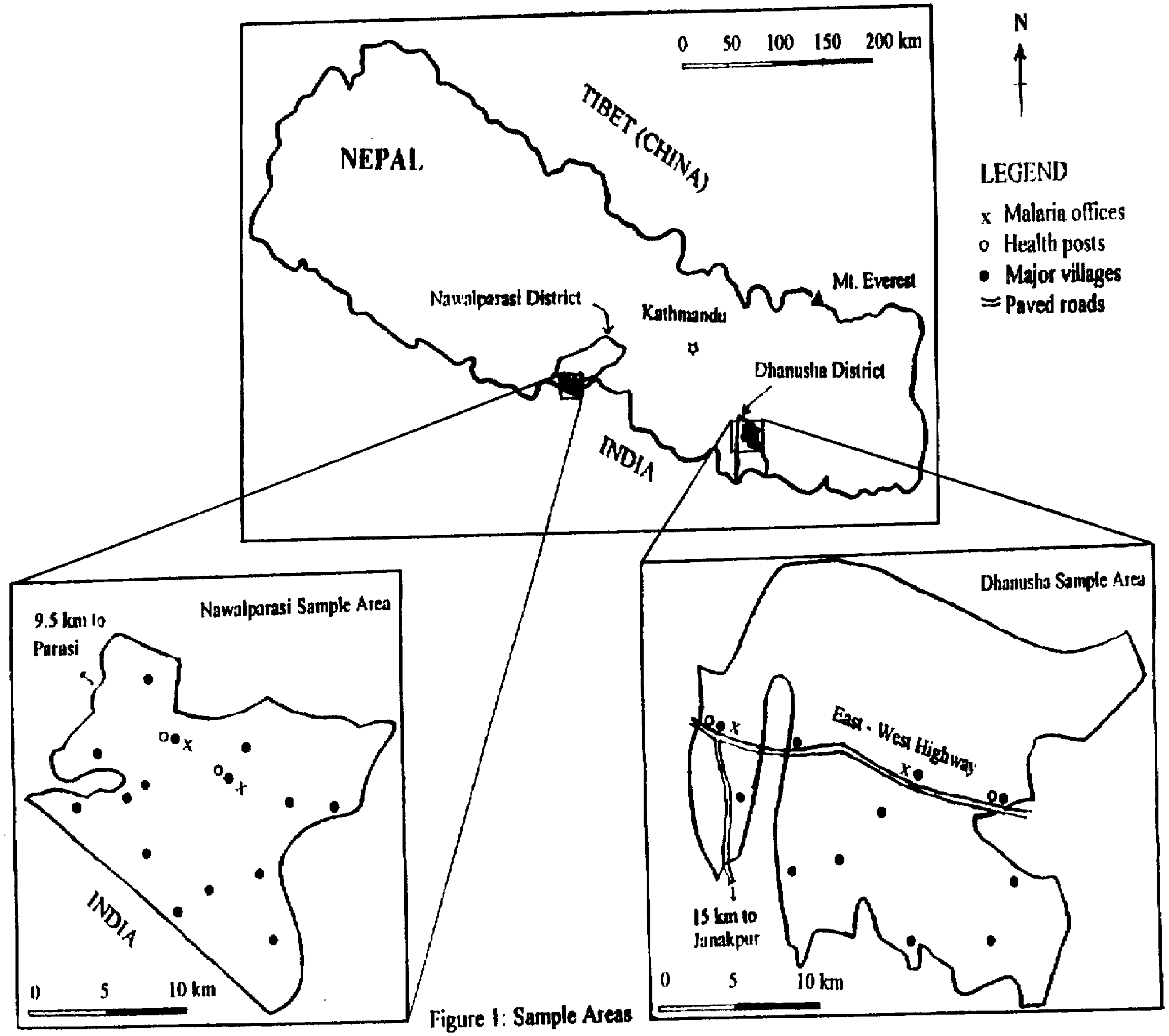

Figure 1: Sample Areas

offices, malaria workers, and malaria volunteers. The DOHS staffs health posts that treat all illnesses, including malaria. There are two types of private providers: private practitioners and faith healers.

Only the initial visit is modeled. We also model choice of provider by type, not the specific provider. Except for location, providers of a given type are quite homogenous in terms of their characteristics, so patients typically visit the closest provider of the type chosen - the provider who can be reached in the minimum amount of time. Columns 2 and 4 of Table 4 report the proportion of patients in Dhanusha and Nawalparasi choosing each type of provider. Note that only 2% of the patients in Dhanusha chose private practitioners as compared to 40% in Nawalparasi.

The NMEO divides each district into a number of areas, and each of these areas has a malaria office where patients can go for treatment. There are four malaria offices in the areas sampled, two in each district. Most villages have a malaria volunteer, and malaria workers visit each house approximately once a month to detect and treat malaria. Therefore, a patient has the option of receiving treatment at home by waiting for the next visit of the malaria worker. Given the visits of the malaria workers, no treatment and self-care are not available options.

Table 1: Days of Wait for Radical Treatment by NMEO Malaria Patients (1984)*

Number of days between blood collection and radical treatment	% of patients in Dhanusha	% of patients in Nawalparasi
7 days or less	72	59
8 to 14 days	22	30
More than 14 days	6	11

*Nepal Malaria Eradication Organization (1987)

The three types of NMEO providers treat only malaria. If an individual has a fever, malaria is suspected and the NMEO providers take a blood sample, which is sent to the district headquarter to test for malaria. This generates a delay between the initial visit and the confirmation of malaria. Because of this delay, NMEO providers initially treat the suspected malaria patient with a standard broad-based treatment that temporarily eliminates symptoms and the potential for transmission, but does not cure the patient, so symptoms and contagiousness are likely to reoccur, sometimes in a matter of days. If the blood sample confirms malaria, the NMEO provider brings to the patient's home a drug treatment tailored to the species of malaria. This radical treatment usually cures the patient. The length of time between the initial visit and final treatment is a function of the waiting time for test results, which can be long. See

Table 1. The wait time depends on the distance and road quality between district headquarters and the site of the initial visit.[15] Travel times are significantly longer in Nawalparasi where rough dirt roads connect the survey area to the district headquarters. In Dhanusha, the paved East-West Highway passes through the middle of the sample area.

The other providers — health posts, private practitioners, and faith healers — treat all kinds of disease, including malaria. The government health posts might refer a patient to a malaria office, but rarely take a blood sample. They typically provide a drug treatment similar to what a patient would receive when initially visiting a NMEO provider.

Private practitioners, present in many villages, diagnose symptoms, use stethoscopes, give injections, and sell drugs. They treat all diseases, but do not take blood samples or conduct laboratory tests. If a private practitioner suspects malaria, he immediately provides a drug treatment that he feels will cure the disease. Since there is no blood test, the treatment might be inappropriate. Private practitioners also provide pain killers and vitamins, which NMEO providers do not. In addition, private practitioners from India cross the border into Nawalparasi and rove from village to village on bicycles soliciting and treating patients.

Finally, every village has a faith healer who neither prescribes nor gives drugs. They perform religious rituals to drive away the evil spirits that cause disease.

Most providers have minimal medical training and at most 12 years of general schooling. NMEO providers have one month of medical training, providers at the health posts have twelve months of medical training, and private practitioners typically apprentice for one year with another practitioner. Faith healers have no medical training, but apprentice with a faith healer.

Malaria volunteers, private practitioners, and faith healers are typically available at their home any time of the day. Malaria offices are open seven hours a day, and health posts four hours a day. Patients have an expectation of when a malaria worker will next visit.

The cost of visiting a provider includes any fees for service or drugs, travel costs, and the opportunity cost of time, including the cost to escort a child. Public providers currently charge no fees for service or drugs. Private

[15]Other factors, such as the frequency of the courier service and the workload at the laboratory, also influence wait time, but these other factors produce similar delays for all patients.

providers do not explicitly charge a consultation fee, but their drug charges implicitly include a fee. Faith healers often require a small offering of food and materials, which is used in the rituals and left with the faith healer. Table 2 reports expected drug charges and other descriptive statistics for the providers and patients. To minimize the influence of a few outlying observations, we use median drug expenses to proxy expected drug charges.[16]

Table 2: Summary Statistics for Patient and Provider Characteristics*

Variable	Dhanusha Area Mean	Std. Dev.	Nawalparasi Area Mean	Std. Dev.
Patient's age in years	26.11	11.73	21.38	12.48
Patient's gender (female 1, male 0)	0.24	0.43	0.27	0.44
Patient's years of schooling	0.84	1.98	1.76	2.65
Patient's household wealth, Rs (houses, land, and livestock owned)	14,887	16,950	38,852	59,596
Patient's household size	5.54	2.35	7.29	3.69
Parasite species infecting the patient (PF 1, PV 0)	0.01	0.10	0.21	0.41
Density of parasites in patient's blood (count per ml)	0.90	0.65	0.78	0.70
One-way travel time to bring patient's blood slide to the district headquarters, hours	1.88	0.81	8.23	1.27
Number of days between the onset of symptoms and when a malaria worker is expected to visit.	10.34	9.70	14.05	10.43
Costs of providers' services				
I. Expected drug charges [median of actual expenses], Rs				
A. Private practitioner	3.50	0.00	10.00	0.00
B. Faith healer	0.00	0.00	3.00	0.00
II. Travel fares, Rs				
A. Malaria office	0.81	0.85	0.00	0.00
B. Malaria volunteer	0.00	0.00	0.00	0.00
C. Health post	1.62	1.02	0.00	0.00
D. Private practitioner	0.15	0.48	0.00	0.00
III. Travel times, hours				
A. Malaria office	1.71	1.07	4.00	2.17
B. Malaria volunteer	1.07	1.20	0.47	0.53
C. Health post	1.82	1.01	4.00	2.17
D. Private practitioner	1.25	0.87	0.93	0.74
IV. Variables related to travel time or cost				
A. Working patient (yes 1, no 0) [domestic work and school are considered work]	0.94	0.24	0.91	0.29
B. Do private practitioners rove around the village of the patient? (yes 1, no 0)	0.00	0.00	0.74	0.44

*Faith healers are available in every village and malaria workers treat at patients' homes, so travel times and fares to these providers are zero. All travel fares in Nawalparasi are zero because there is no bus service in the district. The travel times and fares to the clinics (homes) of private practitioners are zero in those villages where practitioners rove on bicycles and offer on-site treatment. Malaria offices, malaria volunteers, malaria workers, and health posts provide drugs free of charge.

Time spent traveling to a provider is significant and varies significantly by provider type and district. All

[16]We did not find any relation between actual drug expenses and the species of the parasite infecting the patient.

travel in Nawalparasi is by foot or ox cart on dirt roads. The main highway through Dhanusha is paved and has bus service, but the rest of the roads are dirt. Distances were measured along the most generally traveled routes using village maps. These were converted to travel times using the typical travel mode (foot, bus, etc.) for each segment of the route.[17] The mean travel times and bus fares for each provider type are reported in Table 2. Time costs are converted into money costs using the wage rates for farm workers: Rs 1.50 per hour for an adult male, Rs 1.20 for an adult female, and Rs 1.00 for a child.[18]

3. A *Step-Income-effects* Logit Model of Provider Choice

Suppose an individual is infected with malaria and the household is choosing the patient's health care provider from among *J* alternative types of provider. Let U_{ij} be the level of utility the household of patient *i* associates with a visit to provider *j*.[19] Although this utility is completely known to the household, there is an unobserved component, ε_{ij}, from a researcher's perspective, such that

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

The household selects provider *k* if $U_{ik} = Max(U_{i1}, U_{i2}, \dots, U_{iJ})$. Assume that the random terms,

$\varepsilon_i = (\varepsilon_{i1}, \varepsilon_{i2}, \dots, \varepsilon_{iJ})$, are each an independent draw from an Extreme Value distribution function

$F(\varepsilon) = exp(-exp(-\varepsilon))$. This distributional assumption leads to a multinomial logit model of choice where the

[17]Buses travel only on paved road at an average speed of 24kph. Travel by foot and oxcart averages 8 kph.

[18]Market wages are taken as the opportunity costs of time for *working* patients (94% of the sample patients in Dhanusha and 91% in Nawalparasi). Infants, the chronically ill, the very old, and the disabled patients are considered *non-working*, and to be conservative, their value of time is assumed to be zero. As an alternative to this approach, we also estimated the opportunity cost of time both as a proportion of the market wage and as a separate parameter for men, women, and children, but neither generalization improves the explanatory power of the model, and the opportunity cost of time parameters were, as expected, highly correlated with the parameter on residual income.

[19]Preferences are defined for the household and the household chooses the most preferred bundle in its budget set. See Haddad *et al*. (1997) for a review of models of intrahousehold resource allocation in developing countries.

probability that the household of patient *i* chooses provider *j* is[20]

$$(2)\quad \pi_{ij} = \frac{exp(V_{ij})}{\sum_{k=1}^{J} exp(V_{ik})}$$

Let Y_i be the patient's household income, and assume that income is unaffected by the choice of provider.[21] Let P_{ij} be the full cost of the services of provider *j*. Feasibility requires that $(Y_i - P_{ij})$ be nonnegative $\forall i$ and *j*.

Assume

$$(3)\quad V_{ij} = V(\mathbf{Z}_j, \mathbf{S}_i, \mathbf{I}_i, Y_i - P_{ij}),$$

where $\boldsymbol{Z}_j$ is a vector of provider characteristics, $\boldsymbol{S}_i$ is the type and severity of the malaria, $(Y_i - P_{ij})$ is the level of consumption of the numeraire, and $\boldsymbol{I}_i$ is a vector of other patient and household characteristics. Utility maximization requires that this conditional indirect utility function be continuous and non-declining in residual income $(Y_i - P_{ij})$.

Further assume

$$(4)\quad V_{ij} = f(\mathbf{Z}_j, \mathbf{S}_i, \mathbf{I}_i) + g(Y_i - P_{ij}, \mathbf{I}_i).$$

V_{ij} is an additive function of the numeraire that depends on $\boldsymbol{I}_i$, but not on $\boldsymbol{Z}_j$ or $\boldsymbol{S}_i$. Specifically assume

$$(5)\quad g(Y_i - P_{ij}, \mathbf{I}_i) = m_0(\mathbf{I}_i)\,(Y_i - P_{ij}) \text{ if } (Y_i - P_{ij}) \le M_0,$$

$$g(Y_i - P_{ij}, \mathbf{I}_i) = m_0(\mathbf{I}_i)\,(M_0) + m_1(\mathbf{I}_i)\,(Y_i - P_{ij} - M_0)$$
$$\text{if } M_1 \ge (Y_i - P_{ij}) > M_0,$$

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[20]Logit models impose the restrictive IIA assumption; that is, the ratio of the choice probabilities for any two providers is independent of the characteristics of other providers. To partially relax this assumption, a number of nested logit specifications were also estimated, but none significantly increased the explanatory power of the model. Multinomial probit models are another way to relax the IIA assumption, but estimation is difficult when there are more than three provider types. See Akin *et al*. (1995) and Bolduc *et al*. (1996) for multinomial probit models of provider choice.

[21]This is weaker than the standard assumption that income is unaffected by the illness. Our model admits the possibility that contracting malaria can reduce household income. Modeling and estimating how household income is affected by the choice of provider is not possible with our data. A more general model would estimate the length of illness as a function of provider choice, and the impact of illness length on household income.

$$g(Y_i - P_{ij}, \mathbf{I}_i) = m_0(\mathbf{I}_i)\,(M_0) + m_1(\mathbf{I}_i)\,(M_1 - M_0) \\ + m_2(\mathbf{I}_i)\,(Y_i - P_{ij} - M_1) \text{ if } \; M_2 \geq (Y_i - P_{ij}) > M_1,$$

and so on for higher residual income categories, where $m_n(\mathbf{I}_i) \geq 0$ and $M_{(n+1)} > M_n \; \forall n$. The function, $g(Y_i - P_{ij}, \mathbf{I}_i)$, is a step function of $(Y_i - P_{ij})$, where $m_0(\mathbf{I}_i)$ is the marginal utility on the first M_0 units of the numeraire, $m_1(\mathbf{I}_i)$ is the marginal utility on the next $M_1 - M_0$ units of the numeraire, etc.[22] Although the marginal utility of income is a step function of income, the utility from the choice of provider j is continuously increasing in residual income.[23]

This model allows the influence of costs to vary by income category.[24] *CV*s will also vary by income category. The choice probabilities are not a function of the specific household income, rather only the household's income category, so estimation does not require detailed income data or specification of the proportion of that income that is available in the period when a provider is chosen.[25] Note that Equation (5) is not more or less general than assuming a specific continuous-income-effects model

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[22]While this function is a "step" function, there is no requirement that the sequence $m_0(\mathbf{I}_i), m_1(\mathbf{I}_i), \ldots, m_N(\mathbf{I}_i)$ is either monotonically decreasing or increasing, even though many presume it is non-increasing. For example, it might be the case that $m_0(\mathbf{I}_i) > m_2(\mathbf{I}_i) > m_1(\mathbf{I}_i)$. If one restrictively assumes $g(Y_i - P_{ij}, \mathbf{I}_i) = m_0(\mathbf{I}_i)\,(Y_i - P_{ij}) \;\; \forall (Y_i - P_{ij})$, there are *zero income effects*; that is, the choice probabilities and the compensating variations do not depend on income or income category.

[23]It is not differentiable with respect to $(Y_i - P_{ij})$ at the M_n points.

[24]This method of incorporating income effects is noted by Fowkes and Wardman (1988). They refer to it as segmenting the data by income groups.

[25]Continuous-income-effects models require detailed income data and specification of the proportion of income available in the period when a provider is chosen. Dor *et al.* (1987) and Ching (1995) use monthly income, which implies a provider is chosen approximately once a month. Gertler *et al.* (1987) estimate the proportion of available income. Schwartz *et al.* (1988), Mwabu *et al.* (1993), and Ellis *et al.* (1994) use annual income, but determination of the choice period is not crucial in their model because they do not impose a budget constraint.

[e.g. $g(Y_i - P_{ij}, \mathbf{I}_i) = \tilde{m}_0(\mathbf{I}_i)(Y_i - P_{ij}) + \tilde{m}_1(\mathbf{I}_i)(Y_i - P_{ij})^2$]; it is different.[26]

4. The Estimated Model

The log-likelihood function is

(6) $L = \sum_{i=1}^{489} \sum_{j=1}^{6} \mathrm{x}_{\mathrm{ij}} ln(\pi_{ij})$

where x_{ij} is a choice dummy that takes a value of 1 if the household of patient *i* chooses provider type *j*, and 0 otherwise.

The estimated model is of the form

(4a) $V_{ij} = \alpha_{oj} + \mathbf{a}_1'(\mathbf{X}_{\mathbf{1}ij}) + \mathbf{a}_2'(\mathbf{X}_{\mathbf{2}ij}) + g(Y_i - P_{ij}, \mathbf{I}_i)$

where $\mathbf{X}_{\mathbf{1}ij}$ is a vector of provider characteristics (elements of $\mathbf{Z}_j$) interacted with patient characteristics ($\mathbf{I}_i$),

and $\mathbf{X}_{2ij}$ is a vector of provider characteristics interacted with illness characteristics ($\mathbf{S}_i$),

(5a) $$g\left(Y_i - P_{ij}, \mathbf{I}_i\right) = \left(\begin{matrix}\beta_1 + \beta_3\left(1 \text{ if adult male, otherwise } 0\right) \\ +\beta_4\left(\text{household size}\right)\end{matrix}\right)\left(Y_i - P_{ij}\right)$$

$$\text{if } \left(Y_i - P_{ij}\right) \leq M_0$$

and

[26]Assuming continuous income effects is obviously incorrect if individuals have step income effects, and assuming step income effects is incorrect if individuals have continuous income effects. For another example of a model with step income effects, see Morey *et al.* (1997). In that application, choice of monument preservation programs, continuous income data was available, but a step model explained choice better than a continuous-income-effects model.

$$
\begin{aligned}
g\left(Y_i - P_{ij}, \mathbf{I}_i\right) &= \begin{pmatrix} \beta_1 + \beta_3\left(1 \text{ if adult male, otherwise } 0\right) \\ +\beta_4\left(\text{household size}\right) \end{pmatrix}\left(M_0\right) \\
&+\begin{pmatrix} \beta_1 + \beta_2 + \beta_3\left(1 \text{ if adult male, otherwise } 0\right) \\ +\beta_4\left(\text{household size}\right) \end{pmatrix}\left(Y_i - P_{ij} - M_0\right) \\
&\text{if } \left(Y_i - P_{ij}\right) > M_0
\end{aligned}
$$

where ($Y_i - P_{ij}$) is assumed to be $\leq M_0$ if household wealth is $\leq$Rs 30,000. Step functions with more and/or different steps were estimated, but none were found significant.

Rs 30,000 is a reasonable estimate of the poverty line. In rural areas, poverty is almost universal among landless households and marginal farmers (those owning less than 2.5 acres of farm land). 100% of landless households and 96% of marginal farmers have household wealth less than Rs 30,000. By this estimate of poverty, 78% of the surveyed households are poor. The household's estimated marginal utility of income is a function of whether the household is poor, its size, and the patient's gender.

Table 3 lists the specific provider and household characteristics in the model and reports their estimated parameters and asymptotic t-statistics. Likelihood ratio tests confirm the significance of all of the included variables, both individually and collectively. Cost, that is, residual income, is the most significant determinant of choice, and the impact of cost on choice is greater for the poor, and for women and children.

Households where the patient is a male have, across the board, a lower estimated marginal utility of income than household where the patient is a female, supporting the evidence that males are more important in the Nepalese family. An explanation is that sickness of a family member casts a pale over the household depressing the enjoyment the household receives from the consumption of goods and services, and, in a male-dominated society, the effect is strongest when the patient is the male head of household. However, this is a cautious interpretation. Because our model assumes income is independent of the choice of provider, we can not estimate the influence of provider choice on income as a function of the patient's gender, which also might cause provider choice to vary by gender.

Table 3: Parameter Estimates

Variables	Parameter	Estimate	t-statistics
Intercept on malaria office	α_{0mo}	4.0879	8.7
Intercept on malaria worker	α_{0mw}	4.1605	9.1
Intercept on malaria volunteer	α_{0mv}	3.7675	8.5
Intercept on health post	α_{0hp}	1.8725	4.6
Intercept on private practitioner	α_{0pp}	2.4069	4.4
Intercept on faith healer (normalized)	α_{0fh}	0.00	xxx
(NMEO provider)[a] * (One-way travel time to the district headquarters for lab test)	α_{11}	-0.2990	-4.8
(Malaria worker)[a] * Number of days between the onset of symptoms and when a malaria worker is expected to visit	α_{12}	-0.1214	-6.4
(Malaria worker)[a] * Number of days between the onset of symptoms and when a malaria worker is expected to visit * Child patient (17 years or younger)[a]	α_{13}	0.0339	1.6
(Patient of Nawalparasi)[a] * (Private practitioner)[a]	α_{14}	3.4666	6.0
(Female patient)[a] * (Malaria office)[a]	α_{15}	-1.2485	-2.9
(PF species infection)[a] * (NMEO provider)[a]	α_{21}	-1.2905	-3.1
(Density of parasites in patient's blood) * (NMEO provider)[a]	α_{22}	0.4451	2.2
Residual income (consumption of the numeraire) marginal utility of residual income is $\beta_1 + \beta_4$ (household size) $+(\beta_2$ if not poor) $+(\beta_3$ if the patient is an adult male)	β_1 β_2 β_3 β_4	0.5911 -0.0827 -0.0873 -0.0113	8.9 -2.0 -2.5 -2.0

[a] A dummy variable that takes a value 1 if true, else 0.

Cost sensitivity also decreases with household size. Given the infectious nature of malaria, a larger family may consider itself more at risk of infection by transmission, so willing to spend more for swift treatment. One would expect the opposite for a noninfectious disease.

The second most significant determinant of choice is the expected number of days one would have to wait for a malaria worker to visit the home. The probability of waiting for a malaria worker decreases as the expected number of days increase. However, ceteris paribus, the household will wait longer if the patient is a child.

The more remote the patient's closest NMEO provider is from the district headquarters, the less likely he or she is to choose a NMEO provider, indicating that households place a premium on the speed of treatment. Wait time for the results of the blood test are positively correlated with the travel time to the district headquarters. These travel times are significantly higher in Nawalparasi where the roads are very poor. The probability of choosing a NMEO provider is also smaller for individuals with PF malaria (complicated cases). Such cases are almost nonexistent in Dhanusha but account for 21 percent of the cases in Nawalparasi. Given the severity of this type of malaria, patients do not want to wait for final treatment, and want immediate relief from pain - NMEO providers do not provide pain killers.

Together, these two factors explain much, but not all, of the difference between the shares for NMEO providers in the two districts. Holding constant travel time to the district headquarters and type of malaria, households in Nawalparasi are still more likely to choose a private practitioner. This might be because private practitioners from India cross the border into Nawalparasi and rove from village to village on bicycles soliciting and treating patients.

Ceteris paribus, the probability of choosing a malaria office is smaller for female patients. This might be attributed to a greater hesitation on the part of women in developing countries to visit unfamiliar places or people.[27] Malaria offices are the least familiar of all provider types: they treat malaria only and are typically not the closest provider. In contrast, malaria workers provide treatment in the patient's home, and private practitioners, malaria volunteers, and faith healers are generally local, so known to the patient. Although health posts are often distant, they are familiar because they provide prenatal care, vaccines for children, and contraceptives.

Variables that were tested but found not to be significant determinants of choice include the patient's education level, providers' medical training, and hours available for consultation.

Table 4 reports the predicted shares for each provider type in each district. They closely match the sample

[27]Stone (1986) and Subedi (1989) find social, cultural, and psychological accessibility, or social distance, of providers an important determinant of utilization of health care services in Nepal. In a study specific to women and malaria, Reuben (1993) points to sociocultural and physiological factors that make access to malaria care unequal between men and women in developing countries.

shares, except for malaria offices and malaria volunteers in Nawalparasi. The estimated model correctly predicts 57 % of the actual choices. A modified R^2 indicates that the estimated model is explaining 36% of the choices.

Table 4: Actual and Predicted Shares of Providers, %

Providers	Dhanusha Actual	Dhanusha Prediction	Nawalparasi Actual	Nawalparasi Prediction
Malaria Office	17	18	9	6
Malaria Worker	38	39	19	18
Malaria Volunteer	39	36	22	28
Health Post	2	2	6	6
Private Practitioner	2	2	40	40
Faith Healer	2	2	4	3

5. Estimated Compensating Variations for Health Care Proposals

Consider a proposal that changes provider costs and characteristics for individual *i* from $\{\mathbf{P}_i^0, \mathbf{Z}^0\}$ to $\{\mathbf{P}_i^{'}, \mathbf{Z}^{'}\}$, and consider how much individual *i's* household would have to be compensated to be indifferent between $\{\mathbf{P}_i^0, \mathbf{Z}^0\}$ and $\{\mathbf{P}_i^{'}, \mathbf{Z}^{'}\}$ on the initial visit. Denote this amount $CV_i\left({}^0 \text{ to } {}^{'}\right)$ and our expectation of it $E\left[CV_i\left({}^0 \text{ to } {}^{'}\right)\right]$. If $\{\mathbf{P}_i^{'}, \mathbf{Z}^{'}\}$ is preferred to $\{\mathbf{P}_i^0, \mathbf{Z}^0\}$, $CV_i\left({}^0 \text{ to } {}^{'}\right)$ is positive and can be interpreted as the household's willingness to pay to have the proposal in place for the initial visit. Given the step-income-effects model, and assuming that the change from $\mathbf{P}_i^0$ to $\mathbf{P}_i^{'}$ does not cause the household to either become poor or leave poverty (Morey 1998),

$$(7)\quad E[CV_i\left({}^0 \text{ to } {}^{'}\right)] = \frac{1}{\beta_i}\left(ln\left[\sum_{j=1}^{6}\exp(V_{ij}^{'})\right] - ln\left[\sum_{j=1}^{6}\exp(V_{ij}^{0})\right]\right)$$

where $\beta_i = (\beta_1 + \beta_3 (\text{1 if adult male, otherwise 0}) + \beta_4 (\text{household size}))$ if the household is poor. If the household is not poor, $\beta_i = (\beta_1 + \beta_2 + \beta_3 (\text{1 if adult male, otherwise 0}) + \beta_4 (\text{household size}))$. Note that household income nets out of $(\ln[\sum_{j=1}^{6} \exp(V_{ij}^{\prime})] - \ln[\sum_{j=1}^{6} \exp(V_{ij}^{0})])$.

Each patient household's $E[CV_i(^{0} \text{ to } ^{\prime})]$ is estimated for each of the following four proposals:

(1) installing one malaria office in each village development committee (VDC),

(2) enlisting one malaria volunteer in each village,

(3) upgrading the existing malaria offices with blood testing capabilities, and

(4) replacing the routine monthly surveillance program with Proposal (1) and Proposal (2).[28]

The $E[CV_i(^{0} \text{ to } ^{\prime})]$ are summarized in Table 5.[29] Except for Proposal (4), all of the sample means are significantly greater than zero, but the amounts are not large. Keep in mind that these are not expected compensating variations for avoiding malaria, nor the expected compensating variations for providing a cure. Most individuals in Nepal with malaria will eventually be effectively treated even if none of these proposals is adopted. Rather, these proposals reduce either the cost of treatment or the time until final treatment.

Converted to units of time using the average wage rate for farm workers, the means of the $E[CV]$s for additional malaria offices and malaria volunteers are 16 and 24 minutes for Dhanusha, and 14 and 9 minutes for Nawalparasi. For upgrading the existing malaria offices the mean $E[CV]$s in units of time are 35 minutes for Dhanusha and 2 hours for Nawalparasi.

The confidence interval on the mean $E[CV_i(^{0} \text{ to } ^{4})]$s indicates that one cannot reject the null hypothesis that households are indifferent between the status quo and eliminating the house visits of malaria

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[28]Very few patients have to wait more than 30 days for the arrival of a malaria worker. To represent the withdrawal of the surveillance program under Proposal (4), the number of wait days had to be made large enough to make the probability of choosing a malaria worker effectively zero. With wait set at 100 days, this probability is 0.0002 or less for all patients. Increasing the number of wait days beyond 100 does not change the $E[CV]$.

[29]The confidence intervals are constructed by bootstrapping. Using the estimated parameter values and their variance-covariance matrix, 1000 sets of parameter values are randomly generated. The generated values are then used to estimate 1000 sets of mean $E[CV]$s. The 95% confidence interval is found by excluding the 25 top and bottom estimates.

workers while increasing the number of malaria offices and volunteers to a level where there is a volunteer in each village and a malaria office in each VDC. Given this indifference, whether Proposal (4) should be initiated depends on the relative costs of the status quo versus Proposal (4), and the secondary benefits of the status quo: in the absence of surveillance visits, some patients may remain untreated and, for others, treatment may be delayed, increasing the overall risk of transmitting infection. The mean $E[CV]$s for Proposal (4) by income and gender indicate no adverse distributional implications.

Table 5: Estimated $E[CV]$s for Health Care Proposals (Rs)

Proposal	Dhanusha Mean $E[CV]$	Dhanusha 95% Confidence Interval	Nawalparasi Mean $E[CV]$	Nawalparasi 95% Confidence Interval
1. One Malaria Office in Each VDC	0.41	0.34 to 0.49	0.35	0.28 to 0.44
2. One Malaria Volunteer in Each Village	0.60	0.52 to 0.67	0.23	0.19 to 0.27
3. Upgrade Existing Malaria Offices with Blood Testing Capability	0.88	0.52 to 1.30	3.07	1.66 to 4.91
4. Replace Surveillance by Proposals 1 and 2	0.23	-0.07 to 0.46	0.17	0.00 to 0.31

The estimated $E[CV]$s for providing all of the malaria offices with the training and microscopes to test blood are significantly higher than the estimated $E[CV]$s for the other proposals. As explained below, Proposal (3) will also cost less than Proposals (1) and (2). If proposal (3) were initiated, blood samples would not have to go to the district headquarters for testing. This would significantly reduce the delay between a visit to a NMEO provider and final treatment, which would significantly improve the welfare of the patient's household. Mean $E[CV]$ for this proposal is larger in Nawalparasi because it is, on average, more remote. Within a district the $E\left[CV_i\left({}^0 \text{ to } {}^3\right)\right]$ vary significantly across patient households as a function of how far the household's NMEO provider is from the district headquarters.

Multiplying the mean of the $E[CV]$s for each proposal by the number of malaria patients in each sample area (534 in the Dhanusha sample area and 371 in the Nawalparasi sample area), provides a lower bound estimate of how much these malaria households, in aggregate, would pay for the adoption of each proposal.[30] The amounts are small. For proposal (1), it is Rs 220 for the Dhanusha area and Rs 130 for the Nawalparasi area. For proposal (2), it is Rs 320 for the Dhanusha area and Rs 85 for the Nawalparasi area. These amounts are inadequate to pay the yearly salary of even one more NMEO employee; Proposals (1) and (2) would require many more employees.[31] So, Proposals (1) and (2) cannot be justified solely on basis of their benefits to the households of malaria patients. If they are to be justified on benefit-cost grounds, there must be substantial secondary benefits such as significantly reduced rates of contagion to others. The benefits to the household of reduced contagion are included in the

$E\left[CV_i\left({}^{0}\text{ to }{}'\right)\right]$.

For proposal (3), the amount of annual aggregate $E[CV]$ is Rs 470 for the Dhanusha area and Rs 1,139 for the Nawalparasi area. In addition, the cost of transporting the blood slides and results between the malaria offices and the central headquarters would be saved. Assuming there are currently two trips a week from the malaria offices to the central headquarters and that these would no longer be required, Rs 1,578 would be saved in Dhanusha and Rs 2,000 in Nawalparasi.[32] Blood testing is estimated to add only 1.5% - 3% to the workload at each malaria office, and there are two malaria offices in each district.[33] Given such a small percentage increase in workload it is unlikely that labor costs at the malaria offices would increase, but if they did increase 2%, the additional cost would be only Rs 220 per district. However, this would be offset by a decrease in workload at the central headquarters. The employee of each office could be trained to perform the tests in approximately three

[30]The estimated annual aggregate $E[CV]$s are lower bound because they are for the first visit only. Some patients visit providers more than once.

[31]The yearly wage of an unskilled laborer is approximately Rs 5,500. Proposal (1) increases the number of malaria offices from 2 to 11 in Dhanusha and from 2 to 15 in Nawalparasi. Proposal (2) increases the number of malaria volunteers from 19 to 69 in Dhanusha and from 40 to 140 in Nawalparasi.

[32]With blood testing at the district headquarters, at least two round trips per week are required to meet the NMEO goal of delivering radical treatment within seven days of blood collection. In Dhanusha, eliminating a trip saves 2.72 hours, and in Nawalparasi it saves 12.82 hours. The cost savings are estimated by converting these time savings into money terms using the wage rate for unskilled workers and adding bus fares. Note that there is no phone service between the malaria offices and the central headquarters.

[33]Reading a slide takes ten to fifteen minutes, and on average, the employee of the each malaria office would have to read approximately four slides per week.

months at a cost of Rs 2,750 per district.[34] A microscope would have to be purchased for each malaria office at an approximate cost of Rs 6,600. Amortizing these training and equipment costs over 10 years, Proposal (3) passes the benefit-cost test in both districts solely on the basis of the benefits to the patient households.

Now consider drug charges by public provider.[35] If public providers initiate drug charges sufficient to cover drug costs, a malaria patient is expected to pay Rs 1 (an amount worth about 40 minutes of wages) for receiving care from public providers.[36] Table 6 reports NMEO shares with and without these drug charges.

Table 6: Predicted Shares of NMEO Providers with and without Drug Charges, %

District	Among All Patients	Among Gender-Age Groups Male Adults	 Women & Children	Among Income Groups Poor	 Others
Dhanusha					
1. With No Charges	93	93	94	93	94
2. With Charges	91	90	92	91	92
Nawalparasi					
1. With No Charges	52	46	57	58	41
2. With Charges	44	39	48	49	35

In Nawalparasi, proportionately more women, children, and poor use NMEO providers. Drug charges by public providers would divert 2% of total visits in Dhanusha away from NMEO providers and 8% in Nawalparasi. In Dhanusha, the percent diverted does not vary significantly by income or gender. In Nawalparasi, the percent diverted is larger for the poor, and larger for women and children.

Drug charges are regressive in terms of the $E[CV]$s. In Nawalparasi the poor will pay more to avoid them and in Dhanusha they will pay approximately the same amount, so as a percentage of income the poor in both

[34]Individuals with 10 years of schooling are trained by apprenticing with a lab technician for 3 months.

[35]A more general equilibrium analysis would consider all tax implications and consider all possible externalities associated with the imposition of drug charges. For example, if there are no externalities associated with charging for drugs, drug charges combined with a commensurate reduction in taxes must have benefits greater than costs.

[36]Drugs are estimated to cost about Rs 1 per confirmed malaria patient. This estimate is based on (i) Valley Research Group (1995)'s estimate of Rs 3.22 per patient of all kinds in 1993/94, equivalent to Rs 1.47 in 1984/85 prices, and (ii) Mills (1987)'s estimate of Rs 0.62 per suspected malaria patient (not necessarily confirmed) in 1984. Note that private practitioners' drug charges are higher because fees are implicit in the charges. In the analysis we do not consider the general equilibrium tax implications of the government charging for drugs rather than paying for them out of general tax revenue.

districts will pay more to avoid the fee. The poor have a higher marginal utility of income, but are more likely, particularly in Nawalparasi, to choose public providers.

The $E[CV]$s for drug charges combined with Proposals (1) or (2) are all negative; these quality improvements are not sufficient to offset the fee increase.[37] In Nawalparasi, drug charges combined with providing each malaria office with blood testing capabilities, generates a positive $E\left[CV_i\left(^{0}\text{ to }^{\prime}\right)\right]$ for all patient households (mean $E[CV]$ = Rs 2.24), but these vary significantly across households as a function of the remoteness of the household's NMEO providers. In Dhanusha, patient households are, on average, indifferent (mean $E[CV]$ = Rs 0.08), but approximately half are made worse off.

6. **Summary and Conclusions**

This study estimates a multinomial logit model of provider choice by malaria patients in rural Nepal and uses the model to estimate compensating variations for different health care proposals. To admit the possibility that choice and *CV*s are a function of income, the model specifies marginal utility of income to be a step function of income; that is, a function of income categories. The model is utility theoretic and can be estimated without detailed income data.

Characteristics of the household that influence choice include travel costs, income category, household size, the patient's age and gender, and type and severity of malaria. Costs of services are the most significant determinants of choice, and the poor are more cost sensitive. Ceteris paribus, cost sensitivity is less if the patient is an adult male.

Significant provider characteristics include the wait time for initial treatment and the wait time for the results of blood tests. NMEO providers do not provide radical drug treatment until after the species of malaria parasite is confirmed by a blood test, and the wait time for these test results can be substantial. Currently, blood

[37]Drug charges combined with Proposals (1) or (2) are regressive in Nawalparasi because the poor would pay more to stop them, but it is not possible to tell if these actions would be regressive in Dhanusha because there the poor would pay less, so without more detailed income data it is not possible to tell whether the poor would pay proportionally more or less.

work must be sent to the district headquarters for testing.

The expected value of each patient household's compensating variation, *E*[*CV*], is estimated for increasing the number of providers, providing malaria offices with blood testing capabilities, and initiating drug charges with and without these proposals. Drug charges are regressive.

The estimated *E*[*CV*]s for providing all malaria offices with the capabilities to test blood are significantly higher than the estimated *E*[*CV*]s for increasing the number of providers. There is a WTP for swifter final treatment. Providing malaria offices with blood testing capabilities would also cost less. This proposal passes the benefit-cost criteria in both districts.

We have only estimated the patients' choice of provider for their first choice after the onset of symptoms. A richer model would incorporate both the sequence and timing of the patient's provider choices. If better data were available, one could also model how household income is affected by malaria and the choice of provider.

References

Adams, E.K., R. Houschens, G.E. Wright and J. Robbins, 1991, Predicting hospital choice for rural medicare beneficiaries: the role of severity of illness, Health Services Research 26:5, 583-612.

Akin, J.S., C.C. Griffin, D.K. Guilkey and B.M. Popkin, 1986a, The demand for adult outpatient services in the Bicol region of the Philippines, Social Science and Medicine 22:3, 321-328.

______, 1986b, The demand for primary care services in the Bicol region of the Philippines, Economic Development and Cultural Change 34:4, 755-782.

Akin, J.S., D.K. Guilkey and E.H. Denton, 1995, Quality of services and demand for health care in Nigeria: a multinomial probit estimation, Social Science and Medicine 40:11, 1527-1537.

Ali, A., 1991, Status of health in Nepal, Resource Center for Primary Health Care , Nepal and South-South Solidarity, India

Allen, M., 1990, The Hindu view of women, in M. Allen and S.N. Mukherjee, Eds., Women in India and Nepal (Sterling Publishers P. Ltd., New Delhi), 1-20.

Bennett, L., 1983, Dangerous wives and sacred sisters, Columbia University Press, New York.

Bolduc, D., G. Lacroix, and C. Muller, 1996, The choice of medical providers in rural Bénin: a comparison of discrete choice models, Journal of Health Economics 15, 477-498.

Ching, P., 1995, User fees, demand for children's health care and access across income groups: The Philippine case, Social Science and Medicine 41:1, 37-46.

De Bartolomé, C.A.M. and S.A. Vosti, 1995, Choosing between public and private health care: a case study of malaria treatment in Brazil, Journal of Health Economics 14, 191-205.

Department of Health Services, Epidemiology and Disease Control Division, 1994, Report of the annual assessment of the malaria control activities of 1993, Kathmandu.

Dor, A., P. Gertler and J. van der Gaag, 1987, Non-price rationing and the choice of medical care providers in rural Cote D'Ivoire, Journal of Health Economics 6, 291-304.

Ellis, R.P., D.K. McInnes and E.H. Stephenson, 1994, Inpatient and outpatient health care demand in Cairo, Egypt, Health Economics 3, 183-200.

Fowkes, T. and M. Wardman, 1988, The design of stated preference travel choice experiments, Journal of Transport Economics and Policy 22, 27-44.

Gertler, P., L. Locay and W. Sanderson, 1987, Are user fees regressive? The welfare implications of health care financing proposals in Peru, Journal of Econometrics 36, 67-88.

Haddad, L., J. Hoddinott, and H. Alderman (eds.), 1997, Intrahousehold resource allocation in developing countries: models, methods, and policy (The Johns Hopkins University Press, Baltimore).

Herriges, J.A. and C.L Kling, 1997, Nonlinear income effects in random utility models, discussion paper, Department of Economics, Iowa State University.

Lee, H.L. and M.A. Cohen, 1985, A multinomial logit model for the spatial distribution of hospital utilization, Journal of Business and Economic Statistics, 3:2, 159-168.

Litvack, J.I. and C. Bodart, 1993, User fee plus quality equals improved access to health care: results of a field experiment in Cameroon, Social Science and Medicine 37:3, 369-383.

Luft, H.S., D.W. Garnick, D.H. Mark, D.J. Peltzman, C.S. Phibbs, E. Lichtenberg, and S.J. McPhee, 1990, Does quality influence choice of hospital? Journal of the American Medical Association 263:21, 2899-2906.

McFadden, D., 1996, Computing willingness-to-pay in random utility models, discussion paper, Department of Economics, University of California, Berkeley.

Mills, A.J., 1987, Economic study of malaria in Nepal: the cost effectiveness of malaria control strategies, London School of Hygiene and Tropical Medicine, July.

________, 1994, The economic consequences of malaria for household: a case-study in Nepal, Health Policy 29, 209-227.

Morey, E.R., 1998, Two rum uncloaked: nested-logit models of site choice and nested-logit models of participation and site choice, Chapter 4 in: C.L. Kling and H. Herriges, Eds., Valuing the environment using recreation demand models (Edward Elgar Publishing Ltd.).

Morey, E.R., K. Rossman, L. Chestnut and S. Ragland, 1997, Valuing acid deposition injuries to cultural resources, A report prepared for the National Acid Precipitation Program by the University of Colorado and Hagler Bailly Consulting.

Mwabu, G., M. Ainsworth and A. Nyamete, 1993, Quality of medical care and choice of medical treatment in Kenya, an empirical analysis, The Journal of Human Resources 28:4, 838-862.

Mwabu, G., 1989, Nonmonetary factors in the household choice of medical facilities, Economic Development and Cultural Change 37:2, 383-392.

Mwabu, G.M. and W.M. Mwangi, 1986, Health care financing in Kenya: a simulation of welfare effects of user fees, Social Science and Medicine 22:7, 763-767.

Nepal Malaria Eradication Organization, 1987, Annual report of the internal assessment 1986, Kathmandu.

Paul, B.K., 1992, Health search behavior of parents in rural Bangladesh: an empirical study, Environment and Planning A 24, 963-973.

Rathgeber, E.M. and C. Vlassoff, 1993, Gender and tropical diseases: a new research focus, Social Science and Medicine 37:4, 513-520.

Reuben, R., 1993, Women and malaria—special risks and appropriate control strategy, Social Science and Medicine 37:4, 473-480.

Schwartz, J.B., J.S. Akin and B.M. Popkin, 1988, Price and income elasticities of demand for modern health care: the case of infant delivery in the Philippines, The World Bank Economic Review 2:1, 49-76.

Stone, L., 1986, Primary health care for whom? Village perspectives from Nepal, Social Science and Medicine 22:3, 293-302.

Subedi, J., 1989, Modern health services and health care behavior: a survey in Kathmandu, Nepal, Journal of Health and Social Behavior 30, 412-420.

Valley Research Group, 1995, Unit cost study of primary health care, a report submitted to Ministry of Health, Kathmandu.