8629683

Dor, Avi

THE DEMAND FOR HEALTH CARE IN THE IVORY COAST: THE ROLE OF INCOME, TIME AND POLICY IMPLICATIONS

City University of New York PH.D. 1986

University Microfilms International 300 N. Zeeb Road, Ann Arbor, MI 48106

PLEASE NOTE:

In all cases this material has been filmed in the best possible way from the available copy. Problems encountered with this document have been identified here with a check mark __✓__.

1. Glossy photographs or pages _____
2. Colored illustrations, paper or print ______
3. Photographs with dark background _____
4. Illustrations are poor copy ______
5. Pages with black marks, not original copy __✓__
6. Print shows through as there is text on both sides of page ______
7. Indistinct, broken or small print on several pages __✓__
8. Print exceeds margin requirements ______
9. Tightly bound copy with print lost in spine _______
10. Computer printout pages with indistinct print ______
11. Page(s) ___________ lacking when material received, and not available from school or author.
12. Page(s) ___________ seem to be missing in numbering only as text follows.
13. Two pages numbered _______. Text follows.
14. Curling and wrinkled pages ______
15. Dissertation contains pages with print at a slant, filmed as received ________
16. Other ____________________

University
Microfilms
International

THE DEMAND FOR HEALTH CARE IN THE IVORY COAST
THE ROLE OF INCOME, TIME AND POLICY IMPLICATIONS

By

Avi Dor

A dissertation submitted to the Graduate Faculty in Economics in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York.

1986

This manuscript has been read and accepted for the Graduate Faculty in Economics in Satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

September 29, 1986
Date

Michael Grossman
Chair of Examining Committee

September 29, 1986
Date

Michael Grossman
Executive Officer

Robert Shakotko

Salih Neftci

Michael Grossman
Supervisory Committee

The City University of New York

Abstract

THE DEMAND FOR HEALTH CARE IN THE IVORY COAST THE ROLE OF INCOME, TIME AND POLICY IMPLICATIONS

by

Avi Dor

Adviser: Professor Michael Grossman

A standard hypothesis of health economics is that time acts as a rationing mechanism particularly in the absence of prices. Whether this is true is potentially important to health care planners in developing countries who must find new ways to recover costs. This study tests that hypothesis in the context of rural Ivory Coast, where public health care is provided free of charge. Another relevant policy issue is whether income acts as a barrier to entry in the health care market. This study measures the effect of travel time, income and other variables on the demand for the services of doctors, nurses and traditional healers. Three basic questions are asked: What determines the probability that an ill person will obtain any health care? What determines the probability picking each type of health worker? How much health care is obtained?

The first of these questions may be thought of as a dichotomous entry-to-the-market equation, either probit or logit. The second question is answered using a multinomial provider-choice model. Finally, I estimate a conventional demand equation with number of consultations as well as expenditures on medicines as limited dependent

variables. The estimation was carried out separately for infants, children and adults.

Own-time effects found in this study had the expected negative sign and were highly significant. Despite weak evidence of complementarities between nurses and healers, cross-time effect were usually positive and significant. These results suggest that high opportunity costs prevent many people from obtaining needed treatment. On the other hand, low income elasticities, even in the face of positive prices, as in the case of drug expenditures, indicate that ability-to-pay may be less of an obstacle to health care consumption than previously thought.

Acknowledgements

Jacques van der Gaag of the World Bank first suggested that I undertake a study of demand for health care in the Ivory Coast. I would like to express my gratitude to him for motivating my work and providing comments, suggestions and considerable guidance. I would also like to thank Professor Michael Grossman of the City University of New York and the National Bureau of Economic Research who helped me think through many analytical issues with much patience and with typical clarity.

Financial support for this study was provided by the Living Standards Unit of the World Bank.

Table of Contents

List of Tables

List of Figures

I. Introduction

1.1 General Remarks

Besides the social desirability of improving health, the health status of the population is relevant to the economic development of a country for two reasons: First, as an indicator of economic development, it shows the ability and success or failure of a country to provide for the most basic needs of the people (food, adequate sanitary conditions, shelter). The positive correlation between such crude indicators as child mortality and life expectancy on the one hand, and per capita income on the other, is very robust and has been extensively documented (e.g. Preston 1975, 1980; WDR, 1984).

Secondly, health - as a form of human capital - is an input for the further development of a country. There is ample evidence to suggest that health plays an important role in school enrollment and school performance of children (see for instance, Edwards and Grossman 1979, Bartel and Taubman 1979, Cooper and Rice 1976) and in labor supply and productivity of adults (Berkowitz et al. 1983, Grossman 1975, Grossman and Benham, 1974) and on earnings (Luft, 1976). Furthermore, high infant and child mortality rates are among the most important factors related to high fertility rates, which in turn play a crucial role in development.

Life expectancies as low as 38 years at birth may be found in the poorest among developing nations such as Guinea and Somalia [1]. In middle income countries which include The Ivory Coast, life expectancies

1. 1982 figures.

average 55 for males and 58 for females. In comparison most developed countries have attained life expectancies well above 70 years of age. Similar disparities exist in infant mortality rates. The highest infant mortality rate in the world exists in Afghanistan where 205 of every 1,000 live born infants die during the first year of life. In the majority of developing countries exhibit infant mortality rates in excess of 90 infants per 1000, compared with average of 10 in the industrial market economies.

In light of the above it is not surprising that improving the population's health features as a major goal on the agendas of many local and national governments in less developed countries (LDCs). Although many other factors are relevant for achieving this goal (adequate food supplies, sanitation, education), providing medical care to those who need it plays a central role in improving health.

Thus, in recent years, there has been a growing awareness of the need to find new sources of finance in order to expand social services in developing countries and in some cases avert their virtual collapse. Whereas funds for capital investments are often available through international donors the public sector must fund new ways to finance operating and maintenance costs, i.e., recurrent costs. Much of the discussion within the World Bank focuses on the usefulness of user fees in the health care sector. (Birdsall 1983, de Ferranti 1985). In most developing countries there appears to be a political consensus in favor of free medical care. The Ivory Coast this is manifested in presidential commitment not to impose fees on medical services. In

Peru, it takes the form of a constitutional guarantee of a "tendency" towards free medical care.

Consequently, government intervention in the health-care sector has often lead to a system that provides medical care free-of-charge or for a price that bears little resemblance to the marginal cost of the service or product. General revenues serve as the major source of financing. Revenues from user charges usually contribute less than 10 percent of recurrent expenditures (Ainsworth, 1983, de Ferranti, 1985).

Unfortunately, in their quest to provide medical care free-of-charge or at very low cost, governments have sacrificed the availability of care in order to maintain affordability. Public budgets have been proven to be insufficient for providing adequate care to the majority of the population. Though other factors have also played a role, it seems fair to say that the combination of highly subsidized care and insufficient general funds has lead to a general structure of the health care sector that has the following characteristics:

(i) Quantity rationing has taken the place of the price mechanism. Where financial resources are insufficient to finance a health-care system that meets the need of the population, effective demand is constrained by the sheer lack of medical facilities, personnel and drugs.

(ii) Available supply is unequally distributed, with a strong urban bias. In many LDCs, doctors, nurses and hospital beds are concentrated in the cities, in spite of the fact that the vast majority of the population lives in rural areas.

(iii) Modern curative care ("high-technology" hospitals, "western" doctors) has won the battle over scarce resources, leaving little to finance preventive activities and basic care. This is particularly damaging in LDCs where the leading causes of death are infectious and parasitic diseases. Many of these diseases can be prevented or treated adequately with relatively cheap and simple techniques.

(iv) With barely enough resources to cover salaries and the most basic drugs, there is no money left for equipment or for maintenance of the existing facilities. Consequently, available resource are used inefficiently (doctors without equipment) and the limited amount of medical care that is provided, is generally of low quality.

In the next subsection we will illustrate this broad characterization of a "typical" health-care sector in a LDC, using data from The Ivory Coast. [1]

1.2 Background Information on The Ivory Coast and its Health Care System

The following section draws heavily from the World Bank Country Economic Memorandum (1986) and van der Gaag (1985): Since independence (1960), The Ivory Coast has seen a steady economic growth, from a level

1. For a more general overview the health care sectors in LDCs see, for instance, de Ferranti 1985, Golladay 1980.

of $145 per capita in 1960 up to $1,207 in 1980 [1], the high point of its economic development. During this period crude health indicators improved significantly. The infant mortality rate decreased from 167 in 1960 to 119 in 1982, while life expectancy at birth increased from 39 to 47 years (Table 1). Still, these indicators are little better than those prevailing in neighboring West African countries which are much poorer, and they compare unfavorably to those of an "average" lower middle income country.

Large differences of health exist within the country. In Abidjan life expectancy was estimated at 56 years in 1979, compared with only 39 years in the rural Savanna regions , and 50 years in the urban Savanna regions. Child mortality rates in rural areas exceed those in Abidjan were twice as high as child mortality prevailing in rural areas.

Table 1.1: Health Indicators for The Ivory Coast and lower middle income countries (averages)

	Ivory Coast		Lower Middle Income	
	1960	1980	1960	1980
Crude Death Rate	24	17	20	12
Infant Mortality Rate	167	119	114	89
Child Mortality Rate	40	23	28	13
Life Expectancy at Birth	39	47	45	56

SOURCE: The Ivory Coast Country Economic Memorandum, the World Bank, 1986.

1. All dollar equivalents are in current values for the relevant years.

Part of these differences are likely to be related to the unequal distribution of welfare in The Ivory Coast. Based on the value of total household consumption [1] only 6.4 percent of those in the lowest quintile live in Abidjan, while 29.8 percent of "the poor" live in the Savanna area (Table 2). Just 7.8 percent of "the rich" live in the Savanna, while 42.1 percent of them live in Abidjan. [2] This large, urban-rural welfare gap is paralleled by the distribution of health care facilities.

Table 1.2
The Regional Distribution of Welfare in
The Ivory Coast
Consumption Quintiles, Percentages.

	QUINTILES				
	1	2	3	4	5
Abidjan	6.4	5.9	13.7	27.8	42.1
Other Cities	27.7	17.3	17.4	19.1	18.7
Rural East	17.5	33.2	33.4	23.6	20.9
Rural West	18.5	20.9	19.8	12.6	10.7
Rural Savanna	29.8	22.7	15.7	16.9	7.8
Total	100.0	100.0	100.0	100.0	100.0

SOURCE: Van der Gaag, Lee (1984).

1. Total Household consumption is measured as the sum of cash expenditures on consumption goods, plus the value of home grown produce consumed by the household.

2. For a more extensive assessment of the distribution of welfare in the Ivory Coast see Van der Gaag, Lee (1984).

About 40 percent of the population in The Ivory Coast lives in urban areas. Abidjan alone accounts for a population of 1.6 million, or about 17 percent of the total of 9.3 million (1983). All major hospital facilities are in the cities. The two university hospitals (about 1300 beds in total) are situated in Abidjan, while the five regional hospitals (general hospitals with a capacity of about 275 beds) are found in the cities of Bouaké, Man, Daloa, Abengourou and Korogho. Together these hospital facilities account for 41 percent of all beds. Rural areas are served by small local hospitals, maternity and child care units, dispensaries and mobile health units.

The hospital sector employs 70 percent of all doctors, 45 percent of all midwives and over 50 percent of all nurses. About 60 percent of all doctors are based in Abidjan. The overall health manpower situation is unbalanced. In 1983 there were about 600 doctors, 2200 nurses and 1000 midwives, but virtually no skilled auxiliary workers. [1] Given the current health manpower training system, the World Bank projects that the number of western doctors will increase from 6.5 per 100,000 population in 1983 to 7.8 in 2000. The number of nurses per capita will increase from about 24.9 to 26.5. Thus, the already low nurse/doctor ratio of 3.8 will further decrease to about 3.4.

---

1. There is also an unknown number of traditional healers. Furthermore there are about 7000 "journaliers" working in the health care sector, ranging from gardeners and chauffeurs to laboratory assistants and X-ray machine operators. Most of them are unskilled or received informal training only.

All health workers are paid by the government. Medical care is, in principle, provided free of charge. For 1984 the government health budget was 32.6 billion CFAF, or 6.8% of the total budget. [1] More than 75 per cent of this budget is for personnel cost, about 8 percent for drugs and the rest for materials, equipment, maintenance and other operating cost. Current manpower projections indicate that the total health budget will soon be insufficient even to cover personnel cost only, unless the budget grows much faster than other parts of the government budget, or unless other financial resources are found.

The general quality of the existing facilities leaves much to be desired. A 1979 study showed that of the 309 dispensaries, one third was more than 20 years old, only 19 percent had piped in water and just 21 percent had a working water pump. Pharmaceuticals are in short supply and two thirds of the dispensaries, which are supposed to serve as referral centers, lack any means of transportation. Of the 126 Maternal-Child Health Care units (MCH), 45 percent had no water and 31 percent no electricity. Only 20 percent are able to provide preventive services and general health education, though these tasks are supposed to be part of the workload of all MCHs. The two university hospitals in Abidjan have occupancy rates well in excess of 100 percent, but most of the hospitalized patients are just waiting for the arrival of necessary drugs and other supplies and/or for the repair of equipment. In one university hospital two of the six ORs have not been used during the

---

1. Recurrent budget only.

past three years because basic equipment is broken and funds are lacking for replacement.

1.3 Policy Relevance of Demand Analysis

The foregoing discussion clearly illustrates the need to search for additional resources to finance the health care system. One of the most frequently mentioned options is that of charging user fees. [1] The benefits if this option go well beyond revenue raising *per se*. First of all, if goods and services are priced adequately (i.e. are set equal to their marginal costs), society will allocate it's scarce resources efficiently. For instance, simple measures of preventive medical care are likely to get higher priority under a marginal cost-pricing scheme, because the cost of a unit of preventive care is well below that of a unit of curative care. Furthermore, when prices are zero, there is excess demand for certain goods and services, a situation that can be remedied by the introduction of user charges.

The strongest argument in favor of the current policy to provide medical care free-of-charge (or at very low cost), is that it promotes equal access by eliminating financial barriers. However, given the distorted regional distribution of facilities (as illustrated above) the policy does not result in an equitable health care delivery system. In fact, the policy tends to be regressive with most beneficiaries living in the higher income urban areas.

---

1. For a discussion of other options (e.g. many variants of risk sharing) see de Ferranti, 1985.

Nevertheless, the introduction of user fees into a system that is currently providing goods and services free-of-charge raises many questions regarding both the efficiency and the equity of the system. Among them:

(i) For which goods and services are fees desirable? Should the fee be equal to the marginal cost of the product? Can the marginal cost be measured? Should the fee be high enough to recover all cost, or should certain services be subsidized?

(ii) Though money prices are currently zero, the private cost of obtaining medical care can still be substantial. Travel time is often very long and the monetary cost of traveling can be a substantial outlay for poor families. How can user fees be introduced without making the total cost of obtaining medical care prohibitively high?

(iii) Many studies show high income elasticities for medical care. Will poor families be able to pay the price, if money fees are to be set high enough to recover a substantial part of the total cost?

In this paper we will make a start with answering some of these questions. Our focus will be on current health care utilization patterns in rural Ivory Coast. We will investigate the extent of quantity rationing for medical services provided by doctors, nurses and traditional healers, by estimating own and cross time-price elasticities for these services. We will also look at the corresponding income elasticities. Furthermore, we will analyze expenditures on drugs. In principle drugs too can be obtained free of charge (e.g. in a hospital), if available. However, drugs may also be purchased in the private market. Thus, analyzing drug expenditures will shed some light on the ability-to-pay issue.

II. The Demand for Health Care

2.1 Theory

Demand equations for medical care are derived from the maximization of individual utility functions subject to a budget constraint. In its simplest form the model states:

	V	=	$U(M,Z)$
subject to	I	=	$p_1M + p_2Z$
where	U	=	the individual's utility to be maximized
	M	=	medical care
	Z	=	a composite of all other goods and services
	I	=	individual income.
	p_1, p_2	=	respective prices of M and Z

Acton (1975, 1976) modifies the model to include time costs. Consuming a good or a service requires consumers to spend time associated with travel to the market, queuing, and actual consumption (such as the length of a hospital stay or the duration of a consultation). Thus, the "full price" q of a commodity is the sum of the time price and the money price:

$$q = p + tw$$

where t = total length of time devoted to consuming a good or service.

w = the price of time (often represented by a shadow wage rate)

q, t, refer to medical care M, while q_2 and t_2 refer to commodity Z.

Similarly, Acton defines "full income" as the sum of two components, earned income and non-earned income (the latter includes non-wage income such as rents, profits and interest).

As a consequence of entering q_1 and q_2 in the budget constraint in place of p_1 and p_2 Action derives the result that full price elasticity of demand is simply the weighted sum of the time price and money price elasticities.

$$N_p = \frac{p}{q} N$$

$$N_t = \frac{wt}{q} N$$

where N = elasticity of demand for medical care with respect to full price of medical care.

N_p, N_t = elasticity for medical care demand with respect to money price and time price respectively.

On the basis of this result Acton makes the prediction that as the money price of a medical service approaches zero, demand becomes more sensitive to time price. Thus, when medical care is offered free of charge the extent of utilization of services depends entirely on the distance of health facilities from the individual's home and on the opportunity cost of time. [1]

The predictions regarding income elasticity for this model are less robust. Assuming consumers treat medical care as a normal good, the elasticity of demand for medical care with respect to unearned income is unambiguously positive. On the other hand the sign of the wage elasticity is ambiguous. The income effect of a change in the wage rate on the demand for medical care is of course positive. The substitution effect is positive if and only if

$$\frac{wt_2}{q_2 + wt_2} > \frac{wt_1}{q_1 + wt_1}$$

that is, if the time price is a larger proportion of the total price for the compositive good Z, than it is for medical services, M. Therefore, the net effect on the sign of the wage elasticity is ambiguous.

The utility-type models have certain shortcomings. Health status enters the model as an exogenous component of "taste", which in turn determines the utility an individual will derive from medical care. In reality, people, to some extent, are free to choose their level of health, just as they choose the level of consumption of other commodities. Therefore, there is a distinction between the demand for health and the demand for medical care. Medical care as well as the time associated with it, in fact, may be viewed as inputs in the

1. However, it can be shown that this prediction is correct in a double log (in full price) demand function, incorrect with a linear demand function and indeterminant with other demand functions.

"production" of health, where the household, as suggested by Becker (1965), is perceived as a unit of production.

Grossman (1972, 1975) combines both approaches. There is the familiar consumption motive for demand where health enters the utility function. In addition, Grossman introduces an investment motive, so that health services are treated as inputs in the production of healthy days (h).

A well known axiom of price theory is that the marginal cost of a unit of investment (MC) must equal its marginal rate of return (MR). In equilibrium Grossman derives a special case:

$$Mr = \gamma + a_i = r - {}_{i-1}\bar{\Pi} + d_i = MC$$

where γ_i = marginal money rate of return to an investment in health in period i

a_i = marginal psychic return

r = interest rate foregone by not investing in other assets

${}_{i-1}\bar{\Pi}$ = present change in marginal cost from the last period to the current period

d_i = rate of depreciation of health

This fundamental relationship allows Grossman to treat the consumption and investment aspects of health separately. If $a_i = 0$, then no utility is derived from medical care and it can be treated solely as an investment good. Alternatively when we set $\gamma_i = 0$, medical care becomes a pure consumption good.

Another salient feature of Grossman's model is its multiperiodicity drawn from the human capital model of Ben-Porath (1967). There is an initial inherited stock of health capital, which continuously deteriorates over the life cycle. The stock of health can expand only if investment exceeds this depreciation of health. Eventually the rate of depreciation will outweigh investment, health capital will fall below the minimal stock necessary for survival and death will ensue. Multiperiodicity is also embedded in the budget constraint which states that the discounted value of consumption over the life cycle must equal the discounted future income stream. As in the Acton model, the full price of health services incorporates the opportunity cost of time.

According to the consumption model, a fall in the relative shadow price of health would lead consumers to consume more of the "health" commodity and less of the aggregate good, Z. Consequently the demand for medical inputs will rise, and the expected sign of the price elasticity is unambiguously negative.

Wage increases on the consumption model have the same ambiguous effect as in Acton's model. Higher wages raise demand for all normal goods and services, but they also raise the time costs associated with the production of health. If these costs exceeds the time costs of other home production, the demand for health will actually decline. Consequently the demand for the input medical care will also fall. On the other hand if health were not an inferior commodity than an increase in full wealth would raise the demand for health and medical services.

The point of departure of the investment model is the following relationship:

$$H_{i+1} - H_i = I_i - d_i H_i$$

That is, the change in an individual's state of health from period i to period i+1 depends on health investment minus total depreciation of health in period i. The relevant demand curve in the pure investment model is the marginal efficiency of capital (MEC), which shows the relationship between the level of health capital and the rate of return on an investment in health.

The prediction of the wage elasticity from the investment model stands in sharp contrast to the result obtained from the pure consumption model. Rather that the ambiguous wage effect of the latter, we now anticipate an unambiguously positive wage elasticity of demand for health on medical services. An increase in the wage rate raises the monetary value of the marginal product of health. The higher the wage rate the greater the value of an increase in healthy time to an individual. Thus if medical care and the time intensive home input are substitutes, the individual would have an incentive to substitute medical care for the other relatively more expensive inputs. Unlike the price of own time, the price of medical care does not influence the value of the marginal product of health capital. Therefore, the prediction of price elasticity of demand is quite conventional, that is, an increase in the price of medical services lowers the demand for health capital.

In the current study the main interest is in pecuniary and time variables while socioeconomic attributes are taken merely as control variables. Nevertheless, it will be useful to draw some insights from previous work. The Grossman model is the only model that provides rigorously derived predictions regarding the effect of age and education on the demand for health and medical care.

From the health equation given above, it is obvious that a high rate of depreciation of health capital requires a high rate of investment just to maintain the current stock. Since aging is positively correlated with depreciation of health capital, old age unambiguously raises the demand for health. On the other hand the demand for medical care will rise only if the demand for health is inelastic with respect to the cost of investment in health, (interest rate plus rate of depreciation) i.e., it will depend on the slope of the MEC schedule.

The consumption model includes time preference effects as well as depreciation effects. The individual is presumed to face two distinct types of health: present health and future health. Medical purchases would tend to be positively correlated with age if the elasticity of substitution between present and future health were less than unity.[1] Put differently, if present and future health were relatively poor substitutes, individuals would have an incentive to

1. See Grossman (1972a) pp. 94-95

offset health depreciation by increasing investment in the future. To summarize, both models foresee a tendency towards greater demand for health as the individual ages, although the final outcome is ambiguous.

More education is presumed to increase efficiency of home production of health. In simple terms, relatively educated, well-informed people find ways other than formal care to improve their health (via better diets, for example). Consequently, both the investment model and the consumption model predict a negative correlation between education and the demand for formal medical care, provided that the demand for health capital is inelastic with respect to the price of health (i.e. there must be a strong positive association of education with demand for health capital. In the consumption model, there is a further stipulation that the elasticity of wealth with respect to education be equal to or smaller than the elasticity of health with respect to education (a greater wealth elasticity would imply that education causes a relative increase the productivity of home production other than health, thereby raising the relative price of home-produced health inputs. In that case, the final effect of education on the demand on medical purchases is ambiguous). [1]

None of the models makes explicit predictions regarding the effect of sex on health care demand. However, if males tend to be wage earners, with higher opportunity costs then on the basis of utility maximizing models such as Acton's the impact of sex would be ambiguous.

1. Grossman (1972a), pp. 35-37 and pp. 25-28.

Though the models with endogenous health have a firmer theoretical base than those that treat someone's health status as an exogenous random event (see Maurinen, 1982 for a generalization of the Grossman model), the latter approach seems preferable for the current study given the nature of the health status measure available. We only know whether or not an individual experienced an illness or injury during a relatively short period prior to the survey. This health measure is likely to contain many acute health problems, whereas a health measure suitable for the more general approach should represent the long term "stock of health" of an individual. Furthermore, in the more elaborate household production models the distinction between earned and non-earned income is very important (earned income being endogenous). For the current analyses we can not make this distinction, since only a measure of total income is available. Finally, demand for medical care is only measured if the individual suffered from an illness or injury. Thus, in what follows we will analyze the demand for medical care, conditional upon the presence of an illness, and given the household's total income

2.2 Evidence from the Literature

Another common feature of the analyses presented in the literature is the use of cross-section household data. Usually the unit of observation is the individual, by type of care, but sometimes the household is treated as the unit of observation. Furthermore estimates obtained from the various studies are not always comparable. Recent studies often tend to employ limited dependent variable techniques. The estimated coefficients and elasticities obtained from these procedures have a probabilistic interpretation i.e. they pose the question how will a change in a particular variable effect the probability of seeking care? Even when least square techniques are used, the parameters are not strictly comparable when different dependent variables are introduced as measures of the quantity of medical care. In some studies the dependent variable is the number of medical visits, in others, it is expenditures on medical care. Nevertheless, certain general results seem to emerge from the literature. In the United states and other developed countries, money price elasticities tend to be negative but rather small, time price elasticities tend to be negative and significant and income elasticities are positive but generally low. Only a handful of studies of health care demand in developing countries exist. These include Mwabu (1986), Akin et al. (1985), Musgrove (1983) and Heller (1981). Below we highlight some of these studies, emphasizing price elasticities, time effects and income effects.

More often then not, the data lack information on prices of medical goods and services. Consequently, estimates of price elasticities are scarce. Sometimes prices are calculated as actual expenditures divided by the number of visits or by the number of hospital days. (For instance, see Heller 1982). However, with this procedure there is the danger of introducing errors of measurements in the dependent variable (say visits) into the estimation thereby biasing the estimated coefficient.

Using binary logit, Coffey (1983) found the price-elasticity of the probability of obtaining female ambulatory care to be -0.20. Using least square techniques, Phelps and Newhouse (1974a) obtained a price elasticity of -0.14 for physician office visits by individuals. Holtman and Olsen (1978) approximated prices of outpatient services by dividing total household medical expenditures by the number of visits. They report a household price elasticity of -0.12. When visits are adjusted for quality, elasticities are likely to be even smaller. Goldman and Grossman (1978) found that compensated and uncompensated quality adjusted price elasticities of the number of pediatric visits were -.03 and -.05 respectively. Several results are available in developing countries. Akin et al. used a multinominal logit model to test the effect of provider-reported prices on the probabilities of selecting public care and private care. They found significant positive own-price effects on public care and negative, albeit insignificant, own-price effects on private care. These results are attributable to non-seriously ill adults. In the case of seriously ill adults, there is a negative, significant price effect for public care and a positive insignificant price effect for private care. Cross price elasticities were usually negative and statistically insignificant. Using a conditional logit model, Mwabu found a significant negative price effect on the probability of obtaining any type of health care in Kenya. Heller (1981) obtained price elasticities in Malaysia ranging from -0.015 for number of private consultations to -0.04 for all outpatient demand, measured again by number of visits. The cross elasticity of outpatient visits with respect to the money price of private care was -0.15. Akin (1985) et al. found a negative (insignificant) cross-price effect on the probability of obtaining adult private care, and a positive cross-price effect with respect to public care. On the other hand, the price coefficients in the probability-of-public care regression did not have the expected sign. (However, these results were not based on statistically significant coefficients).

These low price elasticities tend to support Acton's prediction that time is an important rationing devise in the demand for medical care. Furthermore, on the basis of statistically significant coefficients, Acton (1973) obtained negative own-time elasticities for public care and private care demand as well as positive cross-time effects. Such results clearly demonstrate that time may assume the role of the conventional price mechanism.

We should bear in mind that in addition to variations in the choice of dependent variables mentioned above, different measures of time-price are used. Often time is measured in natural units (hours or minutes). Other studies have used the theoretically correct variable, i.e. time multiplied by the wage rate. When actual wages are not known, the value of time is obtained from the imputed reservation wage (Coffey, 1983) or from predicted wages (Colle and Grossman 1978, Goldman and Grossman, 1978).

Ideally, the researcher would have information on the length of time associated with consuming the medical service, that is travel time, waiting time at the source of care and treatment time. In practice, this rarely happens. Travel time appears to be the most widely available measure (van de Ven and van der Gaag (1982), Barer and Stoddart (1981). Data on both travel and waiting time intervals are used by Akin (1985), Heller (1981) Goldman and Grossman (1978), Colle and Grossman (1978), and Acton (1973). Holtman and Olsen (1978) employ solely waiting time; Coffey (1983) is the only study we know of that defines the full-time interval (the sum of travel, waiting and treatment time).

Coffey found that the ratio of public to private time-price had a significantly negative effect on the choice of public care versus private care (females only), and a similar effect of time-price of the interviewee's preferred provider on the probability of entering the medical care system. Only a few other studies demonstrate statistically significant negative time effects on demand. When Colle and Grossman (1978) used a binary logit model to predict the probability of utilizing preventive pediatric care, they found a significantly negative effect associated with time-price. Goldman and Grossman (1978) found a significant negative time price effect on the number of pediatric visits. Holtman and Olsen obtained a similar result for actual time and dental visits (but not for doctor consultations). Using number of visits as the dependent variable in a series of Tobit regressions, Acton calculated that own-travel time and waiting elasticities were -0.96 and -0.12 in the case of public care (at clinics and hospital outpatient departments) or -0.25 and -0.050 in the case of private physician care. Significant positive cross-effects were associated only with the travel time variable: 0.33,for public care with respect to private care and 0.64 for private care with respect to public care.

There is ample evidence to suggest that time acts as a rationing device for medical care although it is not always statistically significant. Additional evidence supporting a negative time or time-price effect is presented in van de Ven and van der Gaag (1982), Stoddard and Barer (1982), Goldman and Grossman (1978), and Newhouse and Phelps (1974). Similar results for developing countries are found in Mwabu (1986), Akin et al. (1985) and Heller (1981).

There is occasional evidence supporting positive time effects, but it is never drawn from significant estimates. This is the case of time price and the number of pediatric visits (in both Goldman and Grossman and Colle and Grossman), travel time and number of preventive care consultations (Salkever, 1976) or number of general practitioner consultations (Hershey et al. 1975). Heller (1982) found a negative association of travel time on the probability of choosing public care, but a positive effect of treatment time on demand.

Estimates of income elasticities are more readily available in the literature.In his empirical model Grossman estimated logarithmic demand equations of medical expenditures by adults. An averaging of income elasticities obtained using slightly different income measures yielded a value of -0.146 for the wages and 0.717 for the unearned income. The significant negative effect of wages was not predicted by the Grossman's pure consumption model and is attributed to measurement errors. Evidence supporting positive wage elasticities is found in Acton (1973) and, to a lesser extent, in A:ton (1973) and Newhouse and Phelps (1976). When the decomposition of income into earned and unearned components is ignored the overall, income effect tends to be significant and positive, yet relatively small in developed countries. Income elasticities not exceeding 0.3 are commonly found in the literature for a variety of model specifications. This is shown to be the case for the number of health care visits by individuals (van de Ven and van der Gaag 1982,Acton, 1975), by the household (Holtman and Olsen, 1978) and for aggregates of the population (Benham and Benham, 1975). Similar results were obtained for health care expenditures by individuals (Phelps, 1975). Income elasticities of demand for pediatric care tend to be considerably higher, as shown by Colle and Grossman (1978) and Goldman and Grossman (1978). However, when the consumer is faced with several alternative providers of medical services, certain providers may turn out to be inferior goods with negative income elasticities, as shown by Acton (1975) who compared public with private care. Coffey (1982) gives the very same result in probabilistic terms. That is, a positive income effect on the probability of entering the medical care system, but a substantial negative income elasticity (-0.36) for the choice of public care over private care. We need mention that when a negative association between income and demand for visits is found, it is invariably based upon statistically insignificant coefficients (Coffey, 1983, Stoddart and Barer, 1981).

Comparable evidence from developing countries is sparse but seems to suggest that income elasticities are relatively high. Musgrove (1983) found that in several Latin American countries income elasticities of health care expenditures by households tend to concentrate around unity. We finally mention an income elasticity of 0.88 obtained by Birdsall and Chuhan (1983) using subjective willingness-to-pay questions for medical care in Mali.

In sum: estimates of the price elasticity for the demand for medical care are scarce. Only in a few studies exogenous price information was available. In those cases own price elasticities tend to be small. There is weak evidence to suggest that cross-price elasticities for public and private care in developing countries are similarly low (Heller, 1981). Otherwise, there is virtually no information on cross-price elasticities for various types of providers. Income elasticities have been estimated more frequently, they are low in developed countries, but seem to be fairly large in LDCs. Most of the evidence regarding the role of time, whether measured in terms of monetary value or actual time-units tend to support a negative effect on the utilization of medical care.

2.3 Analytical Framework

In this study we analyze three distinct questions that are relevant to the overall demand for medical care:

(i) If someone is ill, what determines whether or not he or she will obtain any health care at all.

(ii) What determines the type of health care (i.e. practitioner) actually chosen?

(iii) Determinants of the amount of health care obtained.

The first and second issues suggest a discrete choice analytical framework. The third issue calls for traditional demand analysis, where the demand for health care is measured in a continuous fashion. The theoretical basis for demand analysis is highlighted below.

Conventionally the consumer's utility function is stated in the following way.

$$U = U(X_1, X_2)$$

Where X_1 and X_2 denote quantities of each good in a two-good world. Given that utility is subject to the budget constraint,

$$Y = P_1 X_1 + P_2 X_2$$

Y is the income of the consumer and where P_1, P_2 are the respective prices of each good, the following indirect utility function is obtained.

$$U^* = U^*(P_1, P_2, Y)$$

By Roy's identity, maximization of indirect utility yields demand functions of the form [1]

$$X_1 = X_1(P_1, P_2, Y)$$

Using this framework we define a general health care demand function.

$$M = M(P, Y, H, X)$$

1. The proof that Roy's identity generates a demand curve as a function of income and prices is available in numerous places. See for instance Varian, pp. 126-127.

with M number of medical consultations

P a vector of prices, including time prices

Y a measure of income

X a vector of socio-economic variables

H a measure of health capital

Most empirical models presented in the literature use this general framework. It will also serve as the basis of all econometric specifications in the current study.

The specification of demand function in the continuous case is straight forward. The relative merits of Tobit and OLS are discussed in Section IV. The Entry-to-market question is specified as binary probit or a binary logit. The provider choice question is modelled initially in terms of the most general form of multinomial logit often referred to as the universal logit model. (Amemyia 1981). Accordingly, the probability of picking the j'th alternative given by

$$P_j = \frac{e^{\beta_j' x_k}}{\sum_{j=1}^{J} e^{\beta_j' x_k}}$$

Here each of the $\beta_j' X_k$ terms is a function of all the explanatory variables, including prices. The probability choice set associated with each alternative is therefore completely analogous to the conventional demand function. An advantage of this approach is the absence of the assumption of the independence of irrelevant alternatives, which will be discussed shortly.

In the analysis of discrete choice a distinction is made among utility functions associated with each alternative. Furthermore, the random utility maximization (RUM) hypothesis is usually invoked. [1] In the binary case (easily extended to the case of multiple choices), RUM states that, [2]

$$U_1 = V_1 + \epsilon_1$$
$$U_2 = V_2 + \epsilon_2$$

U_1, U_2 are utility associated with each choice, V_1, V_2 are "representative" or constant utility terms observable to the researcher and ϵ_1,ϵ_2 are random, unobservable components of utility which vary across individuals. For convenience, subscripts denoting the individual were suppressed.

An individual will pick the alternative that yields him the most utility. The probability that this individual picks alternative 1 rather than alternative 2 is given by

$$P_1 = \text{Prob}(U_1 > U_1)$$

---

1. See McFadden 1981.

2. For an extention of RUM to the trinomial case see Hausman and Wise (1978).

substitution yields

$$P_1 = \mathrm{Prob}(\varepsilon_2 - \varepsilon_1 < V_1 - V_2)$$

Thus the choice of an alternative (say a particular mode of health care) depends upon differences in representative utilities.

We will assume that any given characteristic affects representative utility in a different ways. Thus, letting Z be a composite of all characteristics

$$V_1 = \beta_1 Z$$

$$V_2 = \beta_2 Z$$

The logistic distribution in the binary case is given by:

$$P_1 = \frac{e^{V_1}}{e^{V_1} + e^{V_2}}$$

May be written in terms of differences in representative utilities, that is:

$$P_1 = \frac{e^{(\beta_1-\beta_2)Z}}{e^{(\beta_1-\beta_2)Z} + 1}$$

$$P_1 = \frac{e^{bZ}}{e^{bZ} + 1}$$

Note that the same procedure gives the probability of selecting the second alternative:

$$P_2 = \frac{1}{1 + e^{b_2 Z}}$$

However, estimation of P_2 is redundant since $b_1 = -b_2$. (In the multinomial case $b_1 = -\sum_{i=2}^{J} b_j$.)

In practice, most computer programs execute maximum likelihood iterations by making the normalization $\beta_2 = 0$. The resulting parameter estimates have the same interpretation as b_1 is the above example. The first question which was stated earlier (market entry) will be analyzed within a binary framework. (P_1 is the probability of seeking health care). The second question (provider choice) is modelled as a problem of multinomial choices. The procedure described here can be easily expanded to several choices. As long as all prices appear in the probability choice set it will yield the universal logit.

However, it is argued, particularly in the transportation literature that the relevant probability choice sets should include a single price, namely, the price of the alternative being considered. (see McFadden, 1982 or Ben Akiva and Lerman, 1985).[1] The argument may be summarized as follows: Faced with a discrete choice problem the individual is no longer characterized by a utility function of the form $U(X_1, X_2)$ which allows for infinite combinations of two goods. Rather, a decision must be made to consume positive amounts of one good, and none of the other. The corresponding utility takes the form $U(X_1, 0)$ or $U(0, X_2)$. The budget constraint corresponds to a corner solution of

1. McFadden terms this as the "translation-invariant probabilistic choice system". In Manski and McFadden, (1981) pp 212.

demand, either $Y = P_1 X_1$ or $Y = P_2 X_2$. Consequently both indirect utility and derived demand will depend only on own-price.

Alternatively, the researcher may envision a different model of representative utility, for instance:

$$V_1 = \beta Z_1 ,$$
$$V_2 = \beta Z_2 .$$

Here, a different value of the characteristic Z is associated with each alternative. On the other hand, this characteristic has the same effect on the representative utility of each alternative. Stated simply, whereas previously we imposed the constraint $Z_1=Z_2$, we are now saying that $\beta_1=\beta_2$. Using the new constraint, a transformation of the binary logit model analogous to that carried out above would lead to a specification called conditional-logit (McFadden, 1973).

$$P_1 = \frac{1}{1 + \sum_{2=j}^{J} e^{\beta(Z_j - Z_1)}}$$

In this model only independent variables which vary across alternatives may enter directly. These are called alternative specific variables (ASV) such as price and travel time associated with each alternative. Other variables, which remain constant across alternatives (generic variables) such as socioeconomic attributes of a decision maker, may enter the model only if interacted with alternative specific dummy variables (ASDV). Another possibility is to interact a generic variable (x) with an ASV, such as cost (c) and enter the difference $c_j x$-

c_1x into the exponent. Note that when socioeconomic variables are interacted with all ASDVs, the conditional logit model becomes computationally identical to a universal logit model with zero restrictions on the cross price coefficients.

The weakness of the conditional logit approach is the property of independence from irrelevant alternatives (IIA). This has also been coined the red bus/blue bus problem. In a nutshell, it states that in the presence of, for instance, 3 alternatives the odds of i being chosen over j are independent of all other attributes, that is:

$$\ln \frac{P_1}{P_2} = \beta(Z_1 - Z_2) \text{ , independent of } Z_3.$$ [1]

If for instance $P_1 = ½$ and $P_2 = ½$, the implication of the IIA property is that when a third alternative is added $P_1 = P_2 = P_3 = 1/3$. However, if the second and third alternatives are very similar, as in the red bus/blue bus example, we would expect the probability of choosing the first alternative to remain unchanged, whereas the probability of choosing any of the remaining (identical) probabilities to be split equally, i.e. $P_2 = P_3 = ¼$,

Thus, the conditional logit model should be applied only when the researcher is convinced that he or she is faced with clearly distinguishable alternatives. This is not the case in the present study. To my knowledge no previous study of demand for medical care in West Africa has ever been undertaken. (Although a study of Kenya has

1. McFadden, 1982

recently been made available.) Consequently we have no a-priori knowledge of how rural inhabitants of the Ivory Coast perceive services rendered by physicians, nurses and traditional healers. The universal logit model, which allows for a flexible pattern of own and cross price elasticities seems a suitable technique at an early exploratory stage. We will return to the IIA property and its implications with regards to the provider choice model in Section IV.

Finally, we mention that the multinomial probit model conforms with assumptions regarding utility functions implicit in the conditional logit model, while remaining free of the IIA property. (Amemyia, 1981.) However, Since the normal distribution, which is the underlying distribution of the probit model, and the logistic distribution are almost identical (Logit is more heavily concentrated at the tails), Logit and Probit yield similar estimates. This is illustrated in section (IV) for the binary case. No attempt has been made here to estimate a multinomial probit model which is computationally burdensome and prohibitively expensive, since multiple integrals must be evaluated. Similarities between the multinomial logit and the multinomial probit estimates in the trinomial case are shown in Hausman and Wise (1978).

III. Data and Summary Statistics

3.1 The ILS - Survey

Data used in this study are drawn from the Ivorian Living Standard Survey (ILSS). This multi-purpose household survey, which aims at measuring many socio-economic factors relevant to the living standards of Ivorian households, [1] was started in February 1985. During the first 12 month period, 1600 households will be interviewed. The next year 50 percent of these households will be reinterviewed and 800 new households will replace the other 50 percent. The survey is scheduled to be conducted on a permanent basis.

The ILSS has many unique features that distinguishes it from the way household surveys are usually conducted in LDCs. Perhaps its most important characteristic, is the timeliness with which data collected in the field are available for analyses. The current analyses is based on information from 902 households interviewed between February 15 and September 6, 1985 of which 535 were classified as rural. Initial cross-tabulations of these data were published in November 1985. [2]

Information on health is collected on all household members in the survey. Further information about health status and health-care utilization is obtained from persons who reported an illness or injury during the four weeks prior to the interview. The ILSS also contains

1. For detailed information on this survey, see Grootaert, 1985.

2. Enquête Permanente Auprès des Ménages; Resultats provisoires 1985. Côte d'Ivoire Ministère de l'Economie et des Finances; Direction de la Statistique.

extensive information on many socio-economic aspects relevant to the demand for medical care. In this study we use total household consumption ("income") as a measure of the household's economic well-being. Variables such as age, sex and years of schooling are also included as exogenous variables.

Health status is indicated by an individual's own assessment of whether or not he suffered from an illness or injury during the relevant period. Table 3.1 shows the percentage of the population that report an illness during this period. Of the 30 percent reporting an illness, about 57 percent obtained some form of medical care. Figure 1 depicts the distribution of care by type of practitioner. While almost two-thirds of those who obtained medical care in Abidjan consulted a doctor, in the villages only 17 percent saw a doctor. Still fewer consulted a traditional healer (12 percent). The vast majority of rural dwellers consult a nurse (66 percent). Information on medical consumption includes the number of visits to each type of provider, expenditures on consultations (if any) and expenditures on drugs.

In addition to household data, the ILSS collects community level information in rural areas. Relevant to the current study is the data on the availability of various types of health care facilities. If a practitioner, say a doctor is not available in the village, the travel time to the nearest doctor is known. When a practitioner is available in the village, travel time is recorded as zero.

3.2 Health Status as Reflected by ILSS

The ILSS enables us to go beyond the generally available mortality and life expectancy data. It contains information about morbidity, such as the incidence and severity of illness in the population, which is given below by age, sex and geographic location. The weakness of these data is that they are based upon subjective assessments of own states of health.

TABLE 3.1
Percentage of individuals who report an illness or injury during the past four weeks; by region, age and sex.

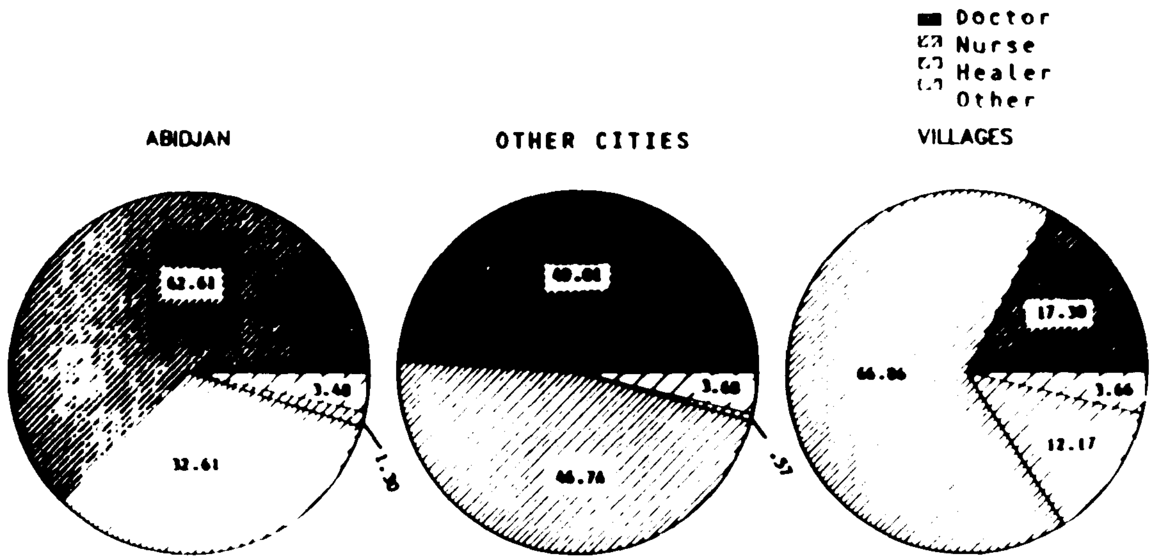
	Abidjan		Other Cities		Villages		Total	
Age	Male	Female	Male	Female	Male	Female	Male	Female
0-5	37.1	39.1	27.9	32.3	28.9	27.8	30.0	30.9
6-15	24.2	21.1	24.9	24.4	17.9	17.9	20.9	19.2
16-35	31.1	23.0	30.7	35.9	22.1	23.8	26.8	29.6
36-49	46.6	37.1	45.2	51.1	45.4	40.4	45.6	41.8
50+	40.0	40.0	64.6	53.2	50.7	50.3	51.7	50.3
Total	32.4	33.0	32.3	33.6	27.9	28.4	29.8	30.4

In terms of self reported health status about thirty percent of the individuals interviewed by the ILSS reported to have suffered from an illness or injury during the four weeks prior to the survey (Table 3.1) 1/. No major sex differentials exist, but there is a distinct age profile. Young children (0-5) show an incidence of illness and injury equal to the overall average, while older children (6-15) show the lowest incidence rate. Adults (16 and over) show a monotonous increase of illness with age.

1/ For the sake of completeness, we present data on individuals who live in Abidjan, Other Cities, and the Villages. Most of our discussion, however, will focus on rural areas, i.e. the Villages.

FIGURE 1

CONSULTATIONS WITH HEALTH CARE PRACTITIONERS: PERCENTAGES



SOURCE: ENQUETE PERMANENTE AUPRES DES MENAGES, 1985.

Table 3.2 Mean Number of Restricted Activity Days during the past four weeks; by region, age and sex

Age	Abidjan		Other Cities		Villages		Total	
	Male	Female	Male	Female	Male	Female	Male	Female
0 -5	5.44	5.19	5.30	5.23	6.69	7.48	6.21	6.50
6-15	4.50	5.29	3.54	3.38	5.08	5.91	4.52	5.14
16-35	4.03	6.04	3.70	5.07	7.95	7.55	5.54	6.45
36-49	3.52	9.26	4.61	6.60	8.41	7.20	6.5[illegible]	7.31
50 +	11.71	8.67	10.10	6.60	10.70	14.19	10.64	12.61
Total	4.95	6.18	4.96	5.15	7.74	8.67	6.55	7.39

Table 3.2 reflects the anticipated decline in health associated with again (as does 3.1): Generally, mean restricted activity days increase with age. The mean restricted activity days in rural areas is 7.7 for males and 8.7 for females compared with little over five days in urban areas. Thus, while the incidence of self-reported health problems appears to be higher in the cities, health problems are on average more severe in rural areas.

Another interesting feature of table 3.2 is excess illness of females compared with males. A notable exception to this trend are persons aged 50 years or over in urban areas. The overall excess female morbidity at that age group is attributed entirely to rural residents. This, however, may be a reflection of attitudes rather than a true measure of ill-health. Males form the major part of the labor force and consequently place a greater value on their time. Excess female mortality continues into old age in rural areas, presumably because retirement occurs there much later.

This straight forward presentation of the data clearly illustrate the severity of health problems in The Ivory Coast. Roughly one-third of the population is ill during any given 4-week recall period, and those who are ill loose about one-quarter of their time due to the illness.

3.3 The Rural Sample

The rest of this study deals strictly with the rural segment of the population. Three age group were considered separately: Infants and toddlers less than 6 years of age, children between ages 6 and 15, adults 16 years of age or older. Summary statistics for adults are shown in Table 3.3; summary statistics for both young age groups are shown in table 3.4. The current stage of the ILS survey encompasses 34 randomly distributed villages and rural cluster areas. In two of these clusters travel time to sources of health care was not known, since the complementary community-survey did not take place there. Since the analysis presented here draws heavily on travel time information these clusters were deleted from the final estimating sample. Of the remaining 32 clusters, 28 had a resident traditional healer, only 8 had a nurse, and none had a medical doctor. The widespread availability of healers explains the small mean of TIMTRAD, travel time from the village to a healer.

Few observations were deleted due to missing values in other variables. There were altogether 2,107 adults of which 737 claimed to have an illness or injury during the four weeks preceding the interview. Approximately one half had at least one consultation with health workers considered here. Of these, 232 consulted a nurse, 77 consulted a doctor and only 46 turned to healers. There were also 2,143 children below the age of sixteen of which 483 had positive sick time during the relevant period. Of these 38 were treated by a doctor, 179 by a nurse and 26 by a healer. Separate summary statistics for each of the child subgroups are available in table 3.4 and section 5.2.

All of the individuals in the sample belong to one of 501 households. The overwhelming majority of households, i.e. 480, were headed by males. The mean age of heads of households is 48.87 (s.d. = 13.96) and their mean years of schooling is only 1.05 (S.D = 2.50). Only the analysis of medicine expenditures employs households as the unit of observation.

TABLE 3.3
Summary Statistics
Rural adults

SAMPLE			
Number of persons, total		2107	
Number of persons with positive sick time		737	
VARIABLES		Mean	Standard Deviation
Endogenous			
Probability of illness or injury	ILL	.35	.47
Probability of seeking consultation with any type of provider	CON a/	.49	.50
number of doctor consultations	DCON	.34	1.73
number of nurse consultations	NCON	1.14	2.67
number of healer consultations	TCON	.25	1.61
Individual expenditures on medicine (CFAF)	MEDPER('000)	5.27	1.06
Exogenous			
Age	AGE	43.86	17.19
Sex (Male = 1, Female = 0),	MALE	.43	.49
Years of Education	EDUC	.88	2.32
Total Household Consumption ("income")	EXP.(MLN)	1.20	1.26
Family Size	SIZE	11.06	10.85
Travel Time to Doctor (Fraction of Hour)	TIMDOC	.89	.63
Travel Time to Nurse	TIMNURS b/	.61	.63
Travel Time to Healer	TIMTRAD	.02	.09
Number of Unrestricted Days	ADAY	18.53	10.07

a/ Henceforth summary statistics refer to persons with positive sick time.

b/ This variable is identical to TIMMOD (travel time to the nearest modern health care provider). There was no case of a nurse being further away than a doctor, although there were several instances of doctors and nurses in the same location.

Table 3.4
Summary Statistics Rural
Children with illness or injury

	Ages 0-5		Ages 6-15	
Sample				
Number of children total	905		1238	
Number of children with positive sick time	262		221	
Variables	Mean	Standard Deviation	Mean	Standard Deviation
<u>Endogenous</u>				
ILLC	.50	.50	.57	.50
PNURS (probability of consulting a nurse)	.40	.49	.33	.47
NCON (number of visits to nurse)	1.03	1.71	1.01	2.59
MEDPER	1.73	4.79	1.21	3.75
<u>Exogenous</u>				
AGE	2.40	1.52	9.57	2.62
MALE	.53	.50	.54	.50
FEDUC (years of education of father)	2.39	3.58	1.27	2.69
EXP (10^6)	1.29	1.38	1.38	1.47
SIZE	12.74	12.02	11.81	11.02
TIMDOC	.78	.59	.82	.61
TIMNURS	.52	.57	.51	.61
TIMTRAD	.02	.10	.02	.09
ADAY	21.33	7.87	22.76	6.75

IV. Estimation Results

4.1 General Comments

This study provides extensive analysis of the demand for primary health care provided by doctors, nurses or traditional healers, to the exclusion of obstetric care. Before turning to the results it will be useful to recapitulate the basic questions we set out to investigate:

i. What determines the probability that an ill person will obtain any health care.

ii. What determines the probability picking each health practitioner.

iii. How much health care is obtained.

The first of these questions may be thought of as a dichotomous entry-to-the-market equation, (either probit or logit) with a health care system that includes both traditional and modern modes of health care. The second question will be answered using a multinomial provider-choice model, whenever the data ill permit it. Finally, we estirate conventional demand equations, whereby the number of consultations is treated either as continuous or limited dependent variable.

Although question i. and ii. imply probability choice sets rather than demand curves per se, the general model described in section II is applicable to all cases:

$$M = M(P, Y, H, X).$$

with M measure of the demand for medical care

P a vector of prices, including time prices

Y a measure of income

X a vector of socio-economic variables

H a measure of health status

Thus the dependent variable M, may be expressed as a binary variable which equals 1 if the individual actually seeks medical care and 0 otherwise, as a series of dummy variables denoting provider choice, or as a measure of utilization in physical units.

In rural areas medical care is provided free-of-charge, so the price vector P contains time prices only. There are two such variables: TIMMOD, the travel time to the nearest place where modern care can be obtained (i.e. doctor or nurse) and TIMTRAD, the travel time to the nearest traditional healer. An increase in either one of these variables is expected to lower the probability that someone seeks medical care. In the provider choice model we make a further distinction between travel time to a nurse (TIMNURS) and travel time to a doctor (TIMDOC).

It is important to note that most of the rural households are farm households, and that most individuals in these households are economically active either as farm workers or in home production activities (fetching wood and water, preparing food, etc.). Consequently, a major part of consumption is comprised on home-grown produce. Consequently, the value of home-grown consumption is included in our measure of total household consumption, in addition to expenditures. Given that consumption usually fluctuates less than income (approximately 40 percent of rural Ivorian households report positive borrowing), this measure is often used as a proxy of long term, "permanent", income.

An individual's health status H, is measured by the number of days during the past four weeks that someone is not restricted in his normal activities. Thus ADAY equals 28 minus the number of days someone was restricted by an illness or injury (as in Table 3.3). Obviously, we expect ADAY to reduce the probability of seeking medical care.

The vector of socio-economic variables X, includes the following variables.

AGE,	age of the individual in years
SEX,	= 1 for male, = 0 for female
EDUC,	years of education
SIZE,	family size
EXP	household consumption, CFAF

Summary statistics of all variables were presented in Table 3.3. [1]

1. The table contains information on additional endogenous variables that will be analyzed in subsequent sections.

V. Estimation of Demand for Health Care

5.1 Estimation Results for Adults

Entry to the Health Care Market

In order to quantify the effect of the exogenous variables on the probability of seeking medical care, we estimated the demand equation in both Logit and Probit form, with CON as the dependent dummy variable (CON = 1 if person consulted with a health practitioner). In Table 4.3 we present the estimation results for adults, i.e. for persons over 16 years of age with positive sick time. We give the coefficients of both models (the β's) with asymptotic T-values. The Logit and Probit coefficients cannot be compared directly. At any rate, the interesting parameters are the slopes, which give the expected change of the probability of seeking health care due to a marginal change in the exogenous variable (the derivative). Formal definitions are given in Appendix A. Throughout this paper slopes are reported for all dichotomous regression.

Because of the similarities between the logistic and normal distributions (the latter being the assumed distribution in Probit) the slopes of the Logit and Probit regressions tend to be very similar. This is shown very clearly in Table 5.1. For convenience the following discussion centers around the Logit estimation.

Age in table 5.1 shows a negative effect (-.030) that is significantly different from zero (t-value = 5.61). Thus, given the value of all other variables, including an individual's health status, the probability of seeking care decreases with age.

Table 5.1
Determinants of decision to seek health care in case of illness; adults in rural areas

	Probit			Logit		
	ß	T	Slope	ß	T	Slope
CONSTANT	1.394	(6.30)	.560	2.280	(6.15)	.570
AGE	-.018	(5.70)	-.007	-.030	(5.61)	-.007
MALE	.104	(1.01)	.042	.157	(.93)	.039
EDUC	-.314	(1.35)	-.013	-.049	(1.31)	-.012
EXP (10^6)	.131	(2.20)	.052	.207	(2.10)	.052
SIZE	-.007	(1.10)	-.003	-.011	(1.02)	-.003
TIMMOD	-.312	(4.00)	-.124	-.515	(3.99)	-.129
TIMTRAD	.254	(.54)	.110	.460	(.56)	.115
ADAYS	-.028	(5.53)	-.011	-.046	(5.46)	-.012
LOG LIKELIHOOD	468.26			468.29		
X^2	84.42			84.74		
INCOME ELASTICITY	0.107			0.107		
TIME ELASTICITY (MODERN)	-0.143			-0.146		

The variables MALE and EDUC do not show a significant impact on demand for health care. Individuals living in households with a relatively high income, however, show <u>ceteris paribus</u> a significantly larger probability of seeking care than their poorer counterparts. On the other hand, the income elasticity at the sample means is only 0.107, comparable to the results usually obtained for industrialized countries, but well below the unit income elasticities obtained by Musgrove (1984).[1]

Family size shows no significant effect and ADAY, the number of "healthy days", has the expected negative impact. Perhaps the most important result is found with respect to the variable TIMMOD, i.e. the travel time to the nearest doctor or nurse. The estimation result implies a time-price elasticity of -.146[2] the sample means. Thus this result confirms the proposition that in the absence of money prices, other private costs of obtaining medical care serve the role of the conventional price mechanism.

It should be stated here that, even though actual fees for medical care are zero, total out-of-pocket expenditures are likely to be positive due to transportation costs. Unfortunately, information on the money cost of travel that is associated with the consumption of medical care was not available in the survey.

The TIMTRAD variable is not significantly different from zero, which is probably due to the small variation in this variable: of the 32 villages in the sample, only 3 did not have a resident traditional healer. In contrast, only 8 villages had their own nurse while none had a doctor.

---

1. Note that Musgrove's estimates refer to health care expenditures while the current analyses deals with the probability of seeking care.

2. Directly comparable estimation procedures are found in Coffey (1983). The time-price elasticity reported there, of entry into the medical care system for low income females in Texas is virtually identical to the above results.

The goodness of fit criterion χ^2, which is given in Table 5.1, is based on the general log likelihood ratio of the form

$$LR = L^*(\hat{\beta})/L^*(0).$$

$L^*(\hat{\beta})$ is the value of the maximized log likelihood using the estimated parameters and $L^*(0)$ is the maximized log likelihood function under the null hypothesis that all β's are equal to zero. It can be shown that $-2 \cdot \ln(LR)$ is approximately distributed as a χ^2_k, where k degrees of freedom are equal to the number of zero restrictions (Wilks, 1962). Throughout this study, χ^2 statistics are sufficiently large to reject the null hypothesis that the estimated β's are equal to zero.

Before showing how the above results hold up when other models of demand for health care are estimated, concerns about selectivity bias should be mentioned. Although data was available for all persons who completed the interview, the estimating sample excludes all healthy people. To see whether this severly biases the sampled data the Probit demand equation was estimated conditional upon the probability of being ill or injured. The procedure yielded small changes in the coefficients and virtually no change in the slopes. Therefore it was concluded that no severe selection bias arose due to the exclusion of health persons. For a detailed description of this procedure and estimation results, the reader may wish to refer to Appendix B.

Provider Choice, a Multinomial Logit Model

In the previous section we analyzed the decision to seek medical care in case of an illness or injury: when ill, an individual either obtained some form of medical care or obtained no care at all. In table 3.3 of the previous section we saw that for all rural adults who obtained medical care, the average number of visits to a doctor is .34, to a nurse 1.14 and to a healer .25 . In this section we first analyze this choice of health-care provider: doctor, nurse or traditional healer. Then we will turn our attention to the number of consultations with each of these providers.

We specify a multinomial logit model of the following form:

$$\ln (P_j/P_o) = \sum_{k=1}^{3} \beta_{jk} t_{jk} + \gamma_j Z$$

with

P_j	The probability of choosing provider j
j = 1	Doctor
j = 2	Nurse, and
j = 3	Traditional healer
t_k	travel time to a given provider
Z	Composite of socioeconomic variables
β_{jk}, γ_j	The corresponding coefficients for choice j

P_o is the default option, i.e. it is the probability of not seeking care when ill, with coefficients normalized to zero. Thus, $\ln(P_i/P_o)$ is the logarithm of the probability of consulting provider j, relative to the probability of not seeking care at all. The composite Z contains the same exogenous variables as in the previous section. The t_k variables denotes travel time, and may be taken as choice-related price variables. Since travel time for the "don't go" option is necessarily zero we are left with 3 = K time-price variables, although the number of possible alternatives (J) is 4.

It is easy to see that the log-odds ratio of any two alternatives depends on all choice related variables and on traits of the decision maker which are common to all choices. Thus the multinomial logit does not exhibit the IIA property.

The interdependence of all alternatives is reflected in the elasticity of P_j with respect to X_k.

$$E_{jk} = (\beta_{jk} \sum_{j=1}^{3} P_{jk} \beta_{jk}) X_k$$

From the above one may calculate own time-elasticities (j = k) cross time elasticities (j ≠ k), or elasticities with respect to a trait of a decisionmaker (replace β by γ). A derivation of various elasticities is given in Appendix B.

Estimation results are given in Table 5.2A. Time prices are represented by the time needed to travel to the nearest doctor, nurse and traditional healer.

All own time-price effects have the expected negative sign. For doctors the coefficient is -2.047 with a T-value of 3.21. Also for doctors the cross time-price effects are positive, though the coefficient for TIMNURS is not significant.

For nurses, in addition to the very significant negative own time-price effect of -0.774, we find positive cross time-price effects. In this instance, however, the coefficient for TIMTRAD is not significant. These results suggest that doctors and traditional healers are substitutes, but nurses and traditional healers are not, which is surprising. The results for healers underscore this surprising result by showing a significant negative cross time-price effect for nurses, i.e. indicating complimentarity between nurses and healers. Obviously, given the relatively small sample size (especially for visits to healers), these results should be judged with caution. More definite statements about the relative position of nurses and healers in the Ivorian health care system should await the analyses of a larger data set.

The income effect for nurses is positive and for healers negative, showing that individuals from more affluent households prefer modern medical care, and that in the economic sense, health care provided by traditional healers is an inferior good. Again we find negative and significant age effects and a positive effect of being a male.

We need not be puzzled by the negative income elasticity for choosing a doctor in Table 5.2B, or by the generally low income elasticity associated with care by doctors compared with nurses. First the coefficient of income in the doctor regression is statistically insignificant. Second, as stated earlier, our proxy for income, namely the total value of consumption by the household, is likely to be highly correlated with earned income. As such, its predicted effect on demand

TABLE 5.2A
Multinomial Logit Model of Provider Choice
Determinants of Choice between Doctor, Nurse, Healer and no Care
Adult in Rural Areas with an Illness or Injury

	DOCTOR		NURSE		HEALER	
	β	T	β	T	β	T
CONSTANT	1.996	(3.16)	1.107	(2.63)	.437	(.59)
AGE	-.036	(3.78)	-.025	(4.28)	-.028	(3.02)
MALE	.546	(1.83)	.092	(.49)	.385	(1.13)
EDUC	.019	(1.31)	-.043	(1.02)	.061	(.76)
EXP (10^6)	-.017	(.10)	.248	(2.41)	-.366	(1.46)
SIZE	-.004	(.25)	-.010	(.86)	.030	(1.30)
TIMDOC	-2.047	(3.21)	.641	(3.53)	.189	(.55)
TIMNURS	.347	(.58)	-.774	(4.29)	-.604	(1.70)
TIMTRAD	2.436	(2.32)	.321	(.32)	-.315	(.15)
ADAY	-0.073	(5.30)	-.044	(4.63)	-.055	(3.37)
LOG_2 LIKELIHOOD			-728.19			
X			160.98			

Table 5.2B
Income and travel time elasticities for the probability of choosing a doctor, nurse or healer (as compared to not seeking care at all)

	Doctor	Nurse	Healer
Income Elasticity	-.091*/.052 [1]*	.229	-.510*
Time-Price Elasticities:			
Doctor	-1.923	.473	.070*
Nurse	.333*	-.352	-.248
Healer	.049	.002*	-.012*

1 Calculated on the basis of model with interaction effects.

* Based on own coefficients not significant at 90 percent level.

is ambiguous. Since in our sample, doctors are located further away, relatively high income earners may be discouraged from seeking services of doctors given the high opportunity costs associated with such a visit. As predicted by the standard utility model, demand might actually decline if the substitution effect resulting from higher time-prices exceeds the income effects. Even a smaller substitution effect will at least dampen the "uncompensated" income effect. For this reason the multinomial logit model was estimated with interaction effects between income and each one of the travel time measures. This procedure did not effect the coefficients of most variables. It did however, result in a positive income effect for doctors (0.003). Elasticity estimates in Table 5.2B correspond to the simpler specification of the model, unless otherwise stated.

Thus the Multinomial Logit Model strongly confirms, and augments, the results obtained from the simpler Probit model: own time-price effects are negative, cross time-price effects are generally positive. The magnitude of these effects is substantially greater than found by Akin et al. in the Philippines (1981, 1985).

We finally note that the impact of socioeconomic variables are generally stable across the entry-to-the-market and provider choice models. In particular, the coefficient of age is always negative and highly significant. The sex effect (of being a male) is always positive, but it is significant only in the case of doctor visits. These results are not compatible with the notion drawn from the standard utility model framework, that individuals with higher opportunity costs of time (e.g. working-age adult males) demand less medical care. Also recall that negative age effects were not predicted by either variant of the Grossman model. The results of this study imply that individuals who are relatively more productive obtain the largest share of medical care in the household.

The coefficient of years of education is negative in the nurse alternative and positive for both the doctor and healer choices but it is never significant. Since nurse patients constitute two thirds of all persons entering the health care market (including those choosing healers), the overall correlation between education and the demand for health is negative. This result is compatible with the notion that education makes people more efficient at "home production" of health, and less likely to require formal medical care. This explanation was also adopted by Acton (1973), who obtained a significant negative education effect on number of outpatient visits. These results are not expected to hold in the presence of an "objective" control variable for the state of health, but as in above mentioned study the measure used here is "subjective", self-perceived health.

An implicit assumption in the above model is that the probability choice set of an individual includes all prices and is therefore analogous to the conventional demand function. This type of probability choice set is found in Small and Rosen (1981).

The preceding multinomial logit model can be made to conform with RUM by imposing zero restrictions on cross price effects. [1]

$$\ln(P_j/P_o) = \beta_j T_j + \gamma_j Z$$

The log odds ratio will not exhibit IIA in any strict sense, since it will always depend on Z, the person trait(s) common to all alternatives. [2] As in the unrestricted case income elasticity of each alternative incorporates income effects of all other alternatives.

On the other hand alternatives are independent with respect to prices. The own-time elasticity becomes:

$$E_j^{P_j} = \beta_j T_j (1 - P_j)$$

As in the case of binary logit, the cross elasticity of the probability of alternative j with respect to travel time to alternative m is:

$$E_m^{P_j} = - \beta_m T_m P_m$$

1. Note that this is computationally identical to a conditional-logit model where socioeconomic variables are interacted with alternative specific dummies.

2. As McFadden (1982 p. 11) states: "... it is not the MNL form per se, but rather the restriction of x_{it} to depend only [my emphasis] on attributes of [alternative] i, that implies the IIA restriction".

It is immediately obvious that the model does not allow for complementarities. Furthermore, cross elasticities of any number of alternatives with respect to price or time of some other alternative m are always constrained to be equal.

In practice, the restricted version of the multinomial logit model is not expected to yield significant changes in the coefficients of the socioeconomic variables. This is not so in the case of travel time variable where actual and spurious correlations (the correlation of TIMDOC and TIMNUR was 0.61), may have biased the estimates in the unrestricted model.

Results of the restricted version of the multinomial logit model are given in Table 5.3A. As anticipated the coefficients of the various socioeconomic variables remain fairly stable compared with the previous MNL model. A notable exception is the disappearance of the negative sign in he income coefficient of the doctor alternative. The changes in travel-time coefficients were, perhaps, smaller than expected. There is no significant change in the own-time effect in the doctor alternative. In the nurse alternative, the coefficient of travel time was reduced by about one half and it approximately doubled in the healer alternative.

New elasticity estimates on the basis of the restricted model are available in Table 5.3B. The cross-time elasticities reflect cross price restrictions. Thus the probabilistic elasticity of visiting a doctor with respect to time to a nurse, for instance, is identical to the probabilistic elasticity of visiting a healer with respect to the same variable. A previously found complementarity between the healer

Table 5.3A: Restricted Multinomial - Logit Model of Provider Choice

	Doctor		Nurse		Healer	
	β	T	β	T	β	T
CONSTANT	2.319	(3.70)	1.476	(3.69)	.221	(.32)
AGE	-.039	(4.04)	-.027	(4.52)	-.033	(3.02)
MALE	.562	(1.89)	.105	(.57)	.367	(1.08)
EDUC	.007	(.12)	-.053	(1.26)	.052	(.65)
EXP (10^6)	.021	(.12)	.267	(2.61)	-.309	(1.24)
SIZE	-.013	(.68)	-.014	(1.25)	.027	(1.14)
TIMDOC	-1.825	(5.24)				
TIMNURS			-.340	(2.46)		
TIMTRAD					-.649	(.33)
ADAY	-.074	(5.38)	-.046	(4.41)	-.056	(3.43)
Log Likelihood			-740.25			
X^2			137.90			

Table 5.3B: Income and Time Elasticities for Restricted Version of Multinomial Logit Model

	Doctor	Nurse	Healer
Income Elasticity	-0.060*	.235	-.458*
Travel-Time Elasticities			
Doctor	-1.531	.095	.095
Nurse	.069	-.318	.069
Healer	.001*	.001*	-.014*

*Based on coefficients not significant at 90 percent level.

and nurse choices has been eliminated, by design. Own-time elasticities have changed only slightly compared with the unrestricted MNL model. The new results reveal substantially weaker substitutability between doctors and nurses compared with the unrestricted MNL model.

t-values tend to be slightly higher in the restricted model. However, the unrestricted model does better in term of goodness-of-fit criteria. Since both models were estimated on the same sample and with the same set of alternative, their likelihood ratios are directly comparable. A commonly used statistic is

$$\rho^2 = 1 - \frac{L(\hat{\beta})}{L(0)}$$

where $L(\hat{\beta})$ is the likelihood function using the estimated coefficient and L(0) is the likelihood function of having no model at all, i.e. when all betas are set equal to zero. In the unrestricted MNL model we obtained $\rho^2 = 0.100$, versus $\rho^2 = 0.085$ in the restricted case. Alternatively, we can construct a likelihood ratio test for the null hypothesis that cross-time effects are zero.

$$\chi^2 = -2 \bullet \ln\left(\frac{L(\hat{\beta}_2)}{L(\hat{\beta}_1)}\right)$$

$\hat{\beta}_1$ denotes the coefficients from the unrestricted model, while $\hat{\beta}_2$ denotes the coefficients from the restricted model. The test yielded a χ^2 value of 24.12, compared with $\chi^2_{30,001} = 50.89$. Consequently the null hypothesis can not be rejected.

Total Member of Consultations with Doctors, Nurses and Healers

In this section we turn to the actual "quantity" of medical care demanded, measured by number of visits to each type of provider. While the dependent variables (DCON, NCON and TCON) may now be interpreted as being continuous, a dichotomy between persons who chose one mode of care (e.g. nurses) and persons who chose another mode or no care at all, persists. The first group exhibits substantial variations in demand whereas the second group is always constrained to zero consultations. For the second group, we have no way of telling how much nursing care would have been demanded, if a decision to seek the services of a nurse had been undertaken. This assymmetry may be dealt with using the Tobit procedure.

The Tobit model is defined here as follows:

$$Y_i = \beta' X_i + u_i \qquad \text{if RHS} > 0$$

$$Y_i = 0 \qquad \text{otherwise}$$

where Y_i is number of visits to a given practitioner by individual i. For individuals with no visits the probability is stated as:

$$P(Y_i = 0) = P(u_i < -\beta' X_i) = 1 - \Phi_i$$

Φ_i is the standard normal distribution function, evaluated at $\beta' X_i / \sigma$

For individuals with positive visits, the probability of the particular number of visits undertaken is simply the normal density function for a random variable $u_i = Y_i - \beta' X_i$

Hence the likelihood function is:

$$L = \prod_{Y=0} (1 - \Phi) \prod_{Y>0} f(u)$$

The likelihood function will yield a single set of coefficients for both visitors as well as none-visitors. [1]

It can easily be shown that $L = \Pi f(u_i)$ yields exactly the same parameter estimators as OLS. Thus OLS is appropriate only when all individuals in the sample have positive visits (that is, when the first term in the right hand side of the Tobit likelihood function disappears).

The results of Tobit regressions on the number of doctor, nurse and healer consultations are reported in Tables 5.5A and 5.5B. For the sake of comparison, similar OLS regressions are shown in table 5.4. A casual glance at the results reveals dramatic differences between the OLS and Tobit coefficients. There are also certain differences between the OLS coefficients and the Tobit marginal effects (slopes) particularly in the education variable and the travel time variables. However, since the OLS estimates are biased we need not pay very much attention to them.

With the exception of the healer regressions Tables 5.4 and 5.5 tend to support findings based on the multinomial logit model. In

---

1. This is not the case when a two-stage procedure of the Tobit model is applied. This procedure, due to Heckman is discussed in Appendix B.

particular, both the TOBIT and the MNL regressions yield significant and negative own-time effects. Furthermore, own-time elasticities calculated on the basis of either model are ranked in the same order of magnitude, that is highly elastic demand for doctor services and relatively inelastic demand for nursing services (refer to Table 5.2B). The parallels between TOBIT and MNL extend to income effects as well. In both models, the coefficient of the income variable is significant only in the nurse regressions. Similarly the income elasticity of demand for nurses is always positive and substantially higher in absolute value than the income elasticity of demand for doctors.

Table 5.4: OLS Regressions, number of visits to a doctor, nurse or healer, in the past 4 weeks Adults in rural areas with an illness or injury

	Doctor		Nurse		Healer	
	β	T	β	T	β	T
CONSTANT	1.275	(4.45)	1.862	(4.25)	.715	(2.61)
AGE	-.006	(1.49)	-.013	(2.16)	-.005	(1.40)
MALE	.312	(2.34)	.138	(.68)	.152	(1.19)
EDUC	-.021	(.71)	-.082	(1.78)	-.001	(.03)
SIZE	-.003	(.41)	-.011	(.87)	.002	(.26)
EXP (10^6)	.005	(.07)	.508	(4.63)	-.041	(.60)
TIMDOC	-.337	(2.51)	.486	(2.36)	.061	(.48)
TIMNURS	-.003	(.02)	-.516	(2.52)	.026	(.20)
TIMTRAD	1.952	(2.90)	.424	(.41)	.935	(1.45)
ADAYS	-.026	(4.07)	-.040	(3.96)	-.019	(3.08)
R^2	.064		.086		.006	
F	5.616		7.621		1.526	

The greatest disparity between the MNL and the TOBIT model is found in the healer regressions. While both models show negative, albeit statistically insignificant income elasticities, the TOBIT regression does not confirm (nor reject) the finding of a negative and significant own-time elasticity calculated on the basis of the logistic regression. We stress that either analysis entails similar implication for health care policy and planning. Better access to modern health care facilities will result in a much higher probability of choosing to consult with a doctor and will dramatically raise the average number of doctor consultations sought by ill or injured individuals. Better access will have a smaller impact on utilization of nursing services but, it will nevertheless have a positive effect on the initial decision to seek nursing services and on the number of consultations with a nurse.Socio-economic variables behave much like they did in the MNL model. The age effect is consistently negative and significant, the sex effect (MALE = 1) is still positive and significant only in the case of doctors, and an overall negative education effect is attributable mostly to nursing patients. None of the education coefficients attain critical t-values.

5.2 Demand for Child Health Care

Before we turn to our analysis of demand for medicine, it will be useful to compare utilization patterns of adult care with utilization patterns of child care. As we previously mentioned, the little evidence that does exist seems to reflect higher income elasticities for pediatric care compared with adult medical care. All of the results

Table 5.5A: Tobit Regression Number of visits to a Doctor, Nurse or Healer, in the past 4 Weeks Adults in Rural Areas With an Illness or Injury

	Doctor			Nurse			Healer		
	β	T	Slope	β	T	Slope	β	T	Slope
CONSTANT	.339	(.15)	.019	-.324	.27	-.096	-8.594	(2.37)	-.474
AGE	-.082	(2.40)	-.005	-.051	2.91	-.015	-.091	(1.79)	-.005
MALE	2.036	(1.89)	.115	.127	.22	.038	1.363	(.85)	.075
EDUC	.028	(.12)	.002	-.191	1.46	-.057	-.148	(.40)	-.008
EXP (10^6)	-.264	(.48)	-.015	1.043	3.76	.308	-1.722	(1.60)	-.095
SIZE	-.013	(.20)	-.001	-.031	.96	-.009	.130	(1.18)	.007
TIMDOC	-7.598	(3.53)	-.429	2.080	3.85	.615	.237	(.15)	.013
TIMNURS	2.567	(1.32)	.145	-2.045	3.73	-.604	-.817	-(.50)	-.045
TIMTRAD	10.433	(2.70)	.590	.857	.30	.253	2.424	(.31)	.134
ADAY	-.207	(4.04)	.012	-.105	3.80	-.031	-.179	(2.30)	-.010
LOG LIKELIHOOD	-360.92			-968.11			-275.64		

Table 5.5B: Income and Travel Time Elasticities from TOBIT Specifications

	Doctor	Nurse	Healer
Income elasticity	-.052*	.326	-.453*
Time-price elasticities			
Doctor	-1.115	.481	.046*
Nurse	.078*	-.324	-.109*
Healer	.039	.005*	.029*

*Based on coefficient not significant at 90% level.

outlined below use the number of physician visits as the dependent variable. The mean age in a study by Inman (1976) was about seven. Estimates of income elasticities there ranged from 0.161 in the case of demand for curative care by non-working mothers to 0.243 the case of preventive care demand by working mothers. Colle and Grossman (1978) found a pediatric care (i.e. ages less than 5) income elasticity of .38. An exceptionally high income elasticity for pediatric medical care is reported in Goldman and Grossman (1978) i.e. 1.32. The last two studies also produced controls for the quality of medical care. Income elasticities with respect to quality indices were generally negligible.

In this study, children were divided into two age groups: infants or toddlers less than six years old and children between ages six and fifteen. The dependent variables in the following regressions are the same as in the adult regressions, with the exception of years of education of the father (FEDUC), which replaces the variable EDUC. Note that FEDUC was preferred over the customary mother's education, in the light of trial regressions (OLS and Logit) which included either one of these correlated variables. The coefficients of both variables consistently turned out to have the same sign, although FEDUC usually possessed higher t-values. For summary statistics the reader should refer to Section III. However, it is useful at this point to compare mean visits for each age group. From Table 5.6 it appears that utilization of modern health care rises with age.

Table 5.6: Means and Standard Deviations of Visits by Age Group and Type of Provider

	Age					
	0-5		6-15		16 +	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
DCON	.16	(.69)	.30	(1.09)	.34	(1.73)
NCON	1.03	(1.71)	1.01	(2.50)	1.14	(2.67)
TCON	.36	(2.34)	.24	(1.76)	.25	(1.61)

As in the analysis of adult health care we begin this study by first posing the question, what determines whether an ill or injured child will obtain health care, not distinguishing between the various types of health workers sought. Since we have established the similarities between the Probit and Logit estimates, it is sufficient to examine the dichotomous logit analysis of the decision to seek health care, shown in Table 5.7. Separate regressions were fitted for the infant and child age groups. The results tend to reaffirm the similarity in medical care utilization patterns between The Ivory Coast and developed countries, that was detected earlier in the paper. In particular, income elasticities appear to be negatively related to age: The probabilistic income elasticity of adults was 0.11 for adults compared with 0.17 for children and 0.26 for infants. On the other hand travel time elasticities with respect to modern health care (TIMMOD) were rather similar across all age groups (-0.15, -0.16, -0.13 respectively), perhaps reflecting the fact that parents or some other adults in the household necessarily devote their own time in order to obtain medical care for a child. Despite the low t-values associated with the coefficients of TIMTRAD in the infant and child logistic regressions, their large magnitude and positive sign merit our attention. It was suspected that the coefficient of TIMTRAD reflected cross-time effects on the overall utilization of health rather than own-time effects. Of 262 infants with medical problems, 105 were attended by nurses, compared with 13 infants who were treated by doctors and merely 8 who were treated by traditional healers. Among the 221 older children with medical problems, the frequencies of such consultations were 74,22 and 29 respectively. (The remaining children in the samples did not obtain any care of this type.) This suggests that the above mentioned regressions are dominated by individuals who were treated by nurses. To verify this, we need to turn to the logit regression for the decision to visit a nurse.

Since each of the two age groups formed a relatively small subsample it was not feasible to repeat MNL estimation for every type of health care provider. In order to avoid the bias resulting from counting actual visits as zero, individuals who were treated by either doctors or healers were deleted from the estimating samples of the nurse-care logits, as reported in Table 5.9. The results confirm the above suspicion. As anticipated own-time elasticities of both young age groups are negative, and the cross-time elasticities are positive. Their values are similar, although not identical to the corresponding elasticities (i.e. with respect to TIMMOD and TIMTRAD) obtained from the health care regression. The income effects associated with the nurse-care regressions are substantially greater than the income effects associated with the health-care model. This is probably due to the fact that the coefficients of the income variable in the health care model reflected positive utilization of healer services by low-income households, which partially offset the relatively strong association of income with nursing care. Comparing probabilistic income elasticities of obtaining nurse-care, for the various age groups, we again discover that income effects rise with age; the MNL analysis of adult utilization yielded an income elasticity of 0.20 compared with 0.28 for children and 0.35 for infants.

Focusing on the amount of child health care actually sought, the small sample size makes it necessary once again to limit the analysis to nurses. Table 5.9 shows results of OLS regressions of the number of visits to a nurse of the past 4 weeks, while Table 5.10 shows Tobit regressions. Note that the variable TIMDOC has been reintroduced into the estimation order to make the foregoing results comparable with the adult demand regressions in the previous section. However, TIMDOC does not exhibit significant coefficients in any of the demand regression for the children subsamples.

The results of the OLS estimation do not reflect the strong negative association between the age category and income elasticity exhibited by the dichotomous model. Income elasticity of nursing visits by children aged 6-15 is 1.25, similar to a result obtained by Goldman

Table 5.7: Determinants of Decision to Seek Health Care Rural Children with Illness or Injury During the Past Four Weeks (LOGIT)

	AGE 0-5			AGE 6-15		
	B	T	Slope	B	T	Slope
CONSTANT	2.071	(3.58)	.500	.127	(.16)	.032
AGE	-.192	(2.04)	-.046	.023	(.42)	.006
MALE	.365	(1.31)	.088	.308	(1.06)	.077
FEDUC	.062	(1.52)	.015	.050	(.90)	.012
EXP (10^6)	.496	(3.02)	.120	.250	(1.64)	.062
SIZE	-.037	(.08)	-.009	-.011	(.56)	-.003
TIMMOD	-.605	(2. 4)	-.146	-.630	(2.43)	-.157
TIMTRAD	5.246	(2.03)	1.266	5.701	(2.07)	1.425
ADAY	-.074	(2.37)	-.017	-.025	(1.21)	.006
LOG LIKELIHOOD		-154.38			-140.29	
χ^2		24.74			25.78	
ELASTICITIES						
INCOME		.260			.171	
TIME						
a. with respect to modern care		-.127			-.159	
b. with respect to traditional care		.026			.059	

Table 5.8: Determinants of Decision to Consult a Nurse Rural Children with Illness or Injury During The Past Four Weeks (LOCIT) [1]

	AGE 0-5			AGE 6-15		
	B	T	Slope	B	T	Slope
CONSTANT	1.429	(2.28)	.357	-.603	(.68)	.145
AGE	-.256	(2.47)	-.064	.060	(.96)	.014
MALE	.515	(1.72)	.128	.274	(.85)	.065
FEDUC	.072	(1.62)	.019	.061	(1.06)	.015
EXP (10^6)	.542	(3.16)	.135	.245	(1.60)	.059
SIZE	-.040	(2.12)	-.010	-.013	(.59)	-.003
TIMMOD [2]	-.580	(2.20)	-.145	-1.080	(3.24)	-.259
TIMTRAD	4.360	(1.72)	1.090	3.452	(1.53)	.828
ADAY	-.055	(2.46)	-.014	-.013	(.53)	-.003
LOG LIKELIHOOD		-134.79			-115.67	
X^2		42.33			26.33	
ELASTICITIES						
INCOME		.352			.280	
OWN-TIME		-.156			-.265	
CROSS TIME		.043			.028	

1. Excluding individuals with doctor or healer consultations.

2. As in the adult regression in 5.1, TIMMOD, time to nearest modern provider is identical to TIMNURS, time to the nearest nurse.

TABLE 5.9: Regression on Number of visits to a Nurse (OLS)
Rural Children with an Illness or Injury during the past four weeks

	AGE 0-5		AGE 6-15	
	B	T	B	T
CONSTANT	1.409	3.63	1.364	.92
AGE	.151	.72	-.437	1.32
FEDUC	.028	.95	-.034	.54
SIZE	-.014	-1.13	-.078	3.51
EXP (10^6)	.260	2.46	.913	5.40
TIMDOC	.168	.70	.315	.84
TIMNURS	-.463	1.89	-.590	.38
TIMTRAD	1.510	1.41	-1.461	.79
ADAYS	-.014	-1.02	-.056	1.49
R^2	.075		.158	
F	2.266		4.415	

and Grossman (1978) for the number pediatric visits in New York City.[1] The income elasticity of adult visits to a nurse 0.54 calculated on the basis of table 9, exceeded the corresponding value for infants (0.33). However, as was previously stated, the OLS estimates are biased. Again we turn attention to the Tobit regressions (Table 5.11)

As in the adult nurse visits regression, the results of the nurse visits regression for the sample of children (Table 5.10) produced statistically significant own time effects. The highest own time

1. Goldman and Grossman use a 2SLS procedure with two equations, demand for visits and demand for quality. Income elasticity of demand for quality was 0.16.

elasticity of demand was found for children aged 6-15, where it is -0.39, calculated at the means, compared with -0.21 for infants aged 0-5 and -0.32 for adults (refer to Table 5.5B). The TOBIT regressions do not mirror the strong negative association between the age group and income elasticity reflected by the corresponding logit regressions. The income elasticity of nursing visits by children aged 6-15 is 0.60, similar to a result obtained by Goldman and Grossman (1978) for the number of pediatric visits in New York City. The income elasticity of infant visits to a nurse was only 0.34, substantially lower than the corresponding value of adults (0.54).

Table 5.10: TOBIT Regression on Number of Visits to a Nurse Rural Children with an Illness or Injury During the Past four Weeks

	Age 0-5			Age 6-15		
	β	T	Slope	β	T	Slope
CONSTANT	.312	(.36)	.124	-2.535	(1.06)	-.750
AGE	-.400	(2.42)	-.159	.157	(.93)	.047
MALE	.580	(1.19)	.231	-.421	(.49)	-.125
FEDUC	.077	(1.18)	.031	.062	(.41)	.019
EXP (10^6)	.680	(2.91)	.271	1.486	(3.73)	.441
SIZE	-.043	(1.54)	-.017	-.120	(2.28)	-.036
TIMDOC	.197	(.37)	.078	.518	(.56)	.154
TIMNURS	-1.076	(1.91)	-.428	-2.632	(2.59)	-.781
TIMTRAD	2.671	(1.19)	1.063	-3.966	(.75)	-1.177
ADAY	-.031	(1.03)	-0.012	-.050	(.82)	-.015
LOG LIKELIHOOD		-360.79			-288.33	
ELASTICITIES						
INCOME		.339			.603	
OWN-TIME		-.216			-.394	
CROSS-TIME						
a. with respect to doctors		.059*			.125*	
b. with respect to healers		.024*			-.024*	

* Based on coefficients not significant at 90% level.

VI. Drug Expenditures

6.1 The Demand for Medicines by Individuals

Respondents in the ILSS were also asked whether they obtained or purchased any medicine as a result of an illness or injury. The highest consumption rate is found in Abidjan, where 75.7 percent of all persons with positive sick time used medicine, followed by smaller cities (65.9 percent) and rural areas (50.9 percent).

From Table 6.1 it appears that both doctors and nurses usually prescribe drugs to their patients. Even among patients of traditional healers the rate of consultation related use of medicine is rather high, i.e. about one third.

Table 6.1: Percentage of Medicine Users among all Persons with Consultations by Type of Health Care Provider

Health Workers	Abidjan	Other cities	Rural	Total
Doctor	88.9	87.3	67.8	83.4
Nurse	78.7	79.4	64.3	69.8
Healer	100.0 [1]	50.0 [2]	30.1	33.7
Total	86.1	83.3	60.7	72.5

1., 2. Note that healers function almost entirely in rural areas. Only 4 patients contacted healers in Abidjan, and 2 in other cities.

Although the lowest rates of consumption of drugs and medicine are found in rural areas, rural utilization of non-prescribed medications exceeds utilization in "other" cities. In rural areas persons who obtained medication without prior consultation, accounted for nearly one-half of all medicine users with positive sick time. Table 6.4 provides a detailed account of this group. The use of self-prescribed medicine ranges from 27.5 percent for males in other cities, to 100 percent for females in Abidjan (there were only seven persons in this group). The rate of self prescription was highest in Abidjan for almost age groups. There are no significant variations by sex with the exception of elderly residents of Abidjan, where the male rate of self prescription was substantially greater than the female rate.

Table 6.2: Self Medication
Percentage medicine users with an Illness or Injury who obtained Medicine without consulting a health Worker

Age	Abidjan Male	Abidjan Female	Other Cities Male	Other Cities Female	Villages Male	Villages Female	Total Male	Total Female
0-5	89.2	46.2	54.6	50.0	35.7	48.3	45.1	48.3
6-15	47.1	54.6	35.3	23.5	43.1	37.5	41.6	37.6
16-35	60.7	48.3	27.5	42.9	42.9	36.8	43.3	63.2
36-49	81.8	100.0	50.0	50.0	53.1	40.3	59.3	46.6
50 +	80.0	33.3	41.2	35.3	39.1	34.8	41.9	84.9
Total	63.5	52.5	37.0	41.1	41.5	39.1	44.8	41.6

The high rate of self-medication suggests that the demand for health and and the need for medical care are only partially explained by visits to health care providers. For this reason we also analyze the demand for medicines by individuals and households.

Though in principle, drugs are provided free of charge, they are often not available in the public sector. Most medicine is obtained in the private market. Since only 52 percent of all adults in rural areas who report an illness or injury have positive expenditures on drugs, we used a Tobit model to estimate the effect of the exogenous variables on drug use. Separate regressions were fitted for individuals and for households. In the first case the dependent variable is individual drug expenditures in the past four weeks due to illness or injury (MEDPER). In the second case, the dependent variable is total household expenditures on drugs or medicine during the past twelve months (MEDEX). Before turning to the estimation results, several comments regarding the specification of the individual expenditures model are warranted.

For each age group we specify two different regressions. In the first specification the explanatory variables include the number of consultations with doctors, nurses and traditional healers (DCON, NCON and TCON). In the second specification we include the corresponding travel time variables (TIMDOC, TIMNURS, TIMTRAD). Although DCON, NCON, and TCON were previously treated as endogenous variables, it may be quite proper to include them as independent variables in the medicine regression. Implicitly, we assume a recursive relationship between the consumption of medicines and the demand for visits, with independent errors of the estimation equations. The model may be written compactly as

$$M = M(N,X)$$
$$N = N(X,T)$$

Where M defines the expenditure function, N is a vector of variables specifying number of visits to each health vector and X is a vector of socioeconomic variables. The demand equation of the i'th category of health worker is defined as $N_i(X,T)$, where T is vector of access variables to each type of worker. The motivation for this regression is found in the descriptive tables which indicate that health workers usually prescribe medicines during consultations. One would like to see whether this relationship is significant in a statistical sense. [1]

If, on the other hand we assume that an error term of any of the demand equations is correlated with the error terms in the drug expenditures equation, then N_i may be substituted into M to yield M = F(X,T) That is, we can obtain a "reduced form" version of the medicine regression, which includes the same set of explanatory variables used to estimate the health care demand equation. Therefore, Tables 6.3-6.5 also present a version of the regression model which excludes DCON, NCON, TCON, but includes the access variables i.e. the travel time measures TIMDOC, TIMNURS, TIMTRAD.

If the government's policy of providing medicines free of charge were, in fact, carried out, one could reasonably expect a negative association between utilization of medical care and drug expenditures by patients in the public sector. However, the first regression in Table 6.3 shows a positive and significant effect of consultations with both types of modern health-care providers on drug expenditures of adults. Since all of these providers in rural areas belong to the public sector, this is further evidence that patients must

---

1. This is likely to be the case, since both expenditures on drugs and health care utilization are affected by the same random component, i.e., illness.

turn to the private market in order to obtain drugs. This finding suggests that typically low incomes in developing countries may not be insurmountable barriers to entry to health care markets. Evidence regarding the income effect on medicine expenditures shown in Table 6.3 confirms the notion that ability-to-pay for medical care may be greater than previously thought. The income elasticity calculated on the basis of the first specification in Table (6.3) (at the sample means) is 0.28 and when the second specification is used income elasticity is about 0.35. Although these results are larger than the probabilistic income elasticity of seeking health care (0.11) obtained earlier, they still fall within the inelastic range, and are similar to the income elasticity of demand for nursing visits which 0.33. Taken together the various estimates suggest that the income effect of demand for health care in The Ivory Coast is similar to the levels found in developed countries. One may argue in that the case of consultations low income elasticities can be explained by the fact that care is provided free-of-charge, but this argument clearly does not apply to drug expenditures.

Expenditures on medicines are negatively associated with visits to traditional healers. This is not surprising since, to the extent that healers prescribe medicines to their patients, their medicines are likely to be inexpensive and of the home grown variety. The large, positive coefficient of the TIMTRAD variable is consistent with negative effect of traditional visits. Note, however, that the elasticity of medicine expenditures with respect to travel time to healers is rather low (about 0.03 at the sample means). We find no statistically significant effect of travel time to modern health practitioners. On the other hand the negative sign of TIMNURS is consistent with the positive effect of nurse visits. This is an important result since nurses provide the bulk of health care in rural Ivory Coast.

Table 6.3: Estimation Results for Expenditures on Medicine during the past 4 weeks by all Rural Adults who Report an Illness or Injury

TOBIT specifications.

	β	T	Slope	β	T	Slope
CONSTANT	-1.732	(.87)	.738	.052	(.02)	.022
AGE	-0.012	(.40)	-.005	-.027	(.87)	-.012
MALE	1.190	(1.18)	.505	1.605	(1.56)	.686
EDUC	-.159	(.70)	-.068	-.239	(1.01)	-.102
SIZE	.110	(1.90)	.047	.118	(1.81)	.046
EXP (10^6)	1.617	(3.20)	.689	1.999	(2.88)	.854
DCON	.895	(3.65)	.381	-	-	-
NCON	.797	(4.78)	.339	-	-	-
TCON	-.728	(1.71)	-.310	-	-	-
TIMDOC	-	-	-	.964	(1.04)	.412
TIMNURS	-	-	-	-1.079	(1.11)	-.461
TIMTRAD	-	-	-	4.998	(.99)	2.134
ADAY	-.234	(4.74)	-.100	-.283	(5.70)	-.121
LOG LIKELIHOOD		-1649.2			-1646.5	
INCOME ELASTICITY		.280			.347	

Tables 6.4 and 6.5 show results of medicine expenditure regressions for infants and children respectively. As in the analysis of demand for medical care reported in section 5.2 the "child" model is identical to the adult model, except that the father's years of education (FEDUC), replaces education of the individual (EDUC). In the

case of children aged 0-5 (Table 6.4) the reduced form version of the medicine expenditure regression exhibits a significant negative effect of travel time to a nurse, which is consistent with the significant and positive coefficient associated with the number of visits to a nurse (NCON) found in the preceding regression. The corresponding coefficients in the 6-15 age category exhibited the same signs (positive for visits, negative for time), although the coefficient of TIMNURS is not significant. Parameters of utilization and access variables associated with the remaining providers tend to be statistically significant (with the exception of TIMDOC in the case of older children) which is positive, but is not a major source of concern, since children were overwhelmingly treated by nurses.

Despite relatively low t-values associated with most of the remaining variables, there are noteworthy parallels between the above mentioned demand analysis and the results shown here. For instance, the age of infants is negatively related to either visits to a nurse or to drug expenditures, whereas the age of older children is positively associated with both measures of health care utilization. The most interesting parallel between the health care demand and drug expenditures analyses, from our perspective, is the fact that in both cases income elasticities of the younger age groups exceed income elasticities of adults.

Table 6.4: Estimation Results for Expenditures on Drugs (in thousands of CFAF) Rural Infants age 0-5 TOBIT Specification

	β	T	Slope	β	T	Slope
CONSTANT	2.157	(1.37)	.932	3.372	(1.62)	1.510
AGE	-.212	(.69)	-.092	-.466	(1.49)	-.208
MALE	-1.070	(1.18)	-.463	-.878	(.95)	-.392
FEDUC	-.082	(.64)	-.036	-.074	(.57)	-.033
EXP (10^6)	1.704	(3.84)	.737	1.947	(4.28)	.869
SIZE	-.123	(2.27)	-.053	-.133	(2.38)	-.060
DCON	.516	(.70)	.223			
NCON	1.019	(3.97)	.440			
TCON	-.945	(1.30)	-.409			
TIMDOC				1.357	(1.35)	.606
TIMNURS				-2.790	(2.62)	-1.246
TIMTRAD				1.195	(.26)	.533
ADAY	-.151	(2.60)	-.065	-.138	(2.43)	.062
LOG LIKELIHOOD		-533.91			-.542.47	
INCOME ELASTICITY		.551			.650	

Table 6.5: Estimation Results for Expenditures on Drugs (in thousands of CFAF) by Rural Children Ages 6-15

TOBIT Specification

	β	T	Slope	β	T	Slope
CONSTANT	1.648	(.70)	.633	.794	(.34)	.303
AGE	.011	(.10)	.004	.038	(.22)	.014
MALE	.900	(1.03)	.346	.651	(.73)	.248
FEDUC	-.019	(.12)	-.007	.021	(.12)	.008
EXP (10^6)	1.536	(3.50)	.590	1.819	(4.31)	.693
SIZE	-.132	(2.30)	-.050	-.146	(2.59)	-.056
DCON	.279	(.73)	.107	-	-	-
NCON	.360	(2.26)	.138	-	-	-
TCON	-.193	(.75)	-.074	-	-	-
TIMDOC	-	-	-	1.395	(1.75)	.532
TIMNURS	-	-	-	-.559	(.58)	-.213
TIMTRAD	-	-	-	-2.931	(.54)	-1.117
ADAY	-.209	(3.40)	-.080	-.209	(3.49)	-.080
LOG LIKELIHOOD		-378.31			-379.91	
INCOME ELASTICITY		.673			.792	

6.2 Demand for Medicines by Households

At last, we turn to drugs and medicine expenditures at the household level. Of the 501 rural households 427 had positive expenditures on medicine during the past twelve months. The mean of annual household expenditures on medicine, in thousands (MEDEX) was 16.828 CFAF, with a standard deviation of 26.149. At the means, medicine expenditures constituted about 1.7 percent of annual household consumption.

Table 6.6 shows the results of three TOBIT regressions on MEDEX. The first regression includes only household variables: Annual household income (EXP) in millions of CFAF, the number of children aged 0-5 (INFANT), number of adults aged 16-49 (ADULT) and the number of elderly household members aged 50 or over (ELDER) and the familiar travel time variables. The independent variables of the second regressions also include socioeconomic characteristics of heads of households. It was reasonable to expect that certain age groups in the household would have a greater effect on total medicine expenditures than others, even though there is no a-priori notion to help us identify such a group. To test the hypothesis that the composition of the household rather than its absolute size determine the level of spending, a third regression was specified in Table 11. It includes SIZE among the independent variables rather than the components INFANT, CHILD, etc. All of the age groups in the first regression have a positive effect on medicine expenditures with the exception of elderly persons. In the second regression, all age groups exhibited a positive effect on expenditures. However, given the low T-values of the coefficients of each age group, no valid interpretation of these results can be made. Other versions of these regressions, no shown here, used total household size (SIZE) rather than the age breakdown. On the other hand, the coefficient of SIZE turned out to be significant at a 99 percent significance level, and was about 0.6. This leads to the conclusion that the age distribution of a household of a given size has little effect on total spending on medication.

The estimated coefficient of EXP remains stable across all specifications, yielding an income elasticity of about 0.48 calculated at sample means. This value falls between adult income elasticities and child income elasticities thereby reflecting the mixed composition of most households. Note that it is well below income elasticities obtained by Musgrove for total health expenditures by Latin American Households. The coefficients of the travel time variables are also stable across both regressions, but only the coefficient of TIMNURS is statistically significant. Comparing the household regression with any of the individual drug regressions, we find that the coefficient of TIMNURS is persistently negative. This suggests that making primary health care more readily available would result in increased consumption of drugs by rural households.

Table 6.6: Estimation Results for Annual Expenditures on Drugs by Rural Households (in thousands of CFAF)

TOBIT specification

	Household Variables			Head of Household Variables			Head of Household Variables		
	β	T	Slope	β	T	Slope	β	T	Slope
CONSTANT	3.302	(1.17)	2.350	6.284	(.79)	4.487	5.919	(.76)	4.219
AGE				-.058	(.48)	-.039	-.042	(.45)	-.030
MALE				-1.134	(.20)	-1.809	-2.416	(.41)	-1.722
EDUC				.743	(1.59)	.531	.817	(1.59)	.583
EXP (10^6)	11.044	(7.92)	7.859	10.994	(8.01)	4.850	11.087	(8.01)	7.903
SIZE							.537	(2.64)	.383
INFANT	.395	(.45)	.281	.200	(.23)	.143			
CHILD	.822	(1.34)	.585	.735	(1.18)	.525			
ADULT	.595	(.92)	.424	.628	(.97)	.449			
ELDER	-.597	(.56)	-.425	.017	(.01)	.012			
TIMDOC	.187	(.08)	.133	.028	(.01)	.020	.656	(.27)	.468
TIMNURS	-7.213	(2.79)	-5.133	-7.004	(2.75)	-5.004	-7.558	(2.95)	-5.388
TIMTRAD	-16.479	(1.52)	-11.727	-17.084	(1.58)	-12.199	-15.826	(1.46)	-11.281
LOG LIKELIHOOD	-2043.0			-2041.5			-2041.5		
INCOME ELASTICITY	.476			.479			.479		

VII. Summary and Conclusions

In Section I it was shown that the health-care system in Ivory Coast fits the mold of an "average" less developed country. Medical care is provided by the public sector free-of-charge, but poor planning has resulted in a top heavy, urban biased delivery system. The descriptive statistics on the regional distribution of health care facilities and on the corresponding utilization patterns strongly suggest that the current system is regressive, benefiting urban dwellers who, on average, are much better off than their rural counterparts.

One frequently mentioned option to obtain additional financial resources for the health care system is the introduction of user fees. While this option has many attractive features, its main drawback is that it may introduce (or enhance) inequality in the health care delivery system by raising financial barriers to access for those who need care the most. On the other hand, it was suspected that in the absence of sufficient facilities in rural area, access to health care is rationed by private costs other than fees such as transportation costs and the opportunity cost of time.

This study set out to investigate two important determinants of the demand for health care namely travel time and income using cross sectional data from the Ivory Coast.

Previous studies from developed countries have consistently shown that income elasticities of demand for medical care are relatively small. There is also ample evidence to suggest that in the absence of money prices, demand in these countries is highly responsive to time costs.

Precious little evidence exists in developing countries. Available studies suggest that behavior of consumers in LDCs may be quite different from modes of behavior commonly found in developing countries. In Latin America, income elasticities were found to be typically high. A study in the Philippines failed to find any evidence of responsiveness of demand to either time prices or money prices.

These results are not readily transferable to all developing countries and certainly not to the Ivory Coast. For instance, Latin America has a well developed private sector whereas rural Ivory Coast has practically no private health care. Thus medical care in rural Ivory Coast is usually available free of charge, a condition which is likely to diminish responsiveness of utilization to income. The hypotheses of zero responsiveness of demand to time and high sensitivity to income were tested at several levels, i.e. in the context of a go/don't go decision, a choice among several alternatives of health care, number of consultations with chosen providers and expenditures on medicines.

This study found that individuals living in households with higher income tend to have a higher probability of obtaining health care. This positive association between income and health care .tilization is attributed mainly to demand for care administered by nurses, who are the major providers in rural areas. The income elasticity of demand for traditional healers was found to be consistently negative, suggesting that traditional medicine is an inferior good. It is difficult to explain, however, why demand for services of physicians exhibits no significant relationship with income. This might be attributable to the small number of observation with positive physician consultations.

In the subsample of rural adults, income elasticities for modern medical care were found to be small and therefore similar to results obtained in developed countries, whereas these results can be explained by zero prices (or third party payments in the developed countries), no such explanation applies to low income elasticities of drug expenditures. Additional evidence of similarities between Ivorian consumers and consumers in developing countries, is the fact that various income elasticities for child care tend to be higher compared with adult medical care. Similar studies of demand for child health care Goldman and Grossman, Colle and Grossman, 1978) indicate that relative high income elasticities are coupled with low responsiveness of quality to income. This suggests that parents attach a greater importance to the quality of care received by their children rather than the actual amount of child care obtained. Unfortunately quality differentials within categories of practitioners could not be identified on the basis of the available data.

All own-time effects found in this study had the expected negative sign and were highly significant, except for the case of healers. Despite weak evidence of complimentarities between nurses and healers (see the MNL model and the healer tobit and the unrestricted regression and the nurse Tobit for children age 6-15), cross-time effect were positive and usually significant. For the most part all types of practitioners appear to be weak substitutes, although doctors and nurses appear to be closer substitutes to each other compared with traditional healers and either modern health worker.

Low income elasticities, even in the face of positive prices as in the case of drug expenditures, indicate that ability-to-pay may be less of an obstacle to health care consumption that previously thought. On the other hand, the overall significance of the negative own time effects and the positive cross time effects suggests that prohibitively high opportunity costs prevent many people from obtaining needed treatment.

Both results are potentially favorable for user-fees schemes. If opportunity costs can be decreased sufficiently vis-a-vis travel time to offset increases in the money price, demand for medical care could be held at current levels. The success of such a scheme will depend on the extent to which additional revenues are in fact devoted to maintenance and possibly expansion of the rural medical care system. Policy makers could alternatively devise a user-fee scheme that will apply only to urban residents exempting the rural population from any payment. Whether this would generate revenues depends to a large on price elasticities in urban markets, which did not fall within the scope of the current study. Finally one would require additional information on marginal costs, currently unavailable, in order to determine the efficacy of user-fees as an instrument of cost-recovery.

Appendix A

Derivation of Elasticities

Note that the coefficients of the Probit and Logit model are not equal to the marginal effects of the independent variables. The latter may be obtained in the following way.

For Probit

$$(1) \quad \frac{\partial}{\partial x_{ik}} \Phi(\beta' x_i) = \phi(\beta' x_i) . \beta_k$$

For Logit

$$(2) \quad \frac{\partial}{\partial x_{ik}} L(\beta' x_i) = \frac{e^{\beta' x_i}}{(1 + e^{\beta' x_i})^2} . \beta_k$$

Where

$\Phi(\beta' x_i)$ = c.d.f. of standardized normal.

$\phi(\beta' x_i)$ = d.f. of standardized normal.

x_{ik} = k-th element of the vector x for the i-th individual.

β_k = k-th element of the coefficient vector β.

Elasticity is defined as the percentage change in variable Y with respect to a percentage change in another variable X. (The individual's subscript is suppressed for convenience) generally:

$$E = \frac{\partial Y}{Y} \Big/ \frac{\partial x}{x} = \frac{\partial Y}{\partial x} \cdot \frac{x}{Y}$$

In the case of discrete choice variables the above formula is given in probabilistic terms, i.e. Y is replaced by the predicted probability of choosing any given alternative. The marginal effect, $\partial Y/\partial x$ is given by (1) or (2), depending on the assumed distribution. We may then ask, what is the change in the <u>probability</u> of choosing alternative j as x varies?

A simplified elasticity formula is available for binary logit.

$$E^{P_j}_{x_{jk}} = \beta_{jk}\, x_{ijk}\, (1-P_j)$$ [1]

This formula also applies to a special variant of the multinomial logit model, where at least some of the explanatory variables are alternative specific. With this specification, the probability of choosing a doctor, for instance, depends only on travel time to a doctor, not on travel time to a nurse or healer. (This model is known as conditional logit, or McFadden's multinomial Logit.)

<u>PROOF</u>

For generality we derive the proof for McFadden's multinomial logit, with J alternatives and at least one alternative specific variable; x_j should be thought of as a vector of dependent variables in

---

1. This may be calculated using the means of $\bar{x}_i$ and the predicted probability ($\hat{P}_i$) or as an average of all individual elasticities.

alternative j, with a corresponding coefficient vector β_j We are interested in the marginal effect of the k'th alternative specific variable.

$$P_j = \frac{e^{\beta_j' x_j}}{\sum_{j=o}^{J} e^{\beta_j x_j}} \quad 1$$

Using the quotient rule:

$$\frac{\partial P_j}{\partial x_{jk}} = \frac{(\Sigma e^{\beta_j' x_j}) \frac{\partial e^{\beta_j' x_j}}{\partial x_{jk}} - e^{\beta_j x_j} \frac{\partial \Sigma e^{\beta_j' x_j}}{\partial x_{jk}}}{(\Sigma e^{\beta_j x_j})^2}$$

$$= \frac{(\Sigma e^{\beta_j' x_j})(e^{\beta_j' x_j})\beta_{jk} - (e^{\beta_j' x_j})(e^{\beta_j' x_j})\beta_{jk}}{(\Sigma e^{\beta_j x_j})^2}$$

Using the definition of P_j:

$$\frac{\partial P_j}{\partial x_{jk}} = P_j \beta_{jk} - P_j^2 \beta_{jk}$$

Hence

$$E_{jk}^{P_j} = P_j \beta_{jk} (1 - P_j). \frac{x_{jk}}{P_j}, \text{ Yielding}$$

1. Binary logit is a special case of MNL, where $P_j = \frac{e^{\beta' x_j}}{1 + e^{\beta x_j}}$

$$E_{jk}^{P_j} = \beta_{jk}\, x_{jk}\, (1-P_j)$$ [1]

In our case, however, each alternative faced the same vector of explanatory variables. (The probability of choosing say, a doctor depended on travel times to each type of practitioner). For convenience we will assume that there is only one dependent variable, x_k. Therefore, the marginal probability of selecting the j'th alternative with respect that variable is

$$\frac{\partial P_j}{\partial x_k} =$$

$$\frac{(\Sigma\, e^{\beta_j x_k})\,(e^{\beta_j x_k})\,\beta_j - (e^{\beta_j x_k}) \cdot (e^{\beta_0 x_k}\,\beta_0 + e^{\beta_1 x_k}\,\beta_1 \ldots + e^{\beta_J x_k}\,\beta_J\,)}{\Sigma\, e^{\beta_j x_k}}$$

Before simplifying invoke the normalization $\beta_0 = 0$ (see Maddala, p. 42), now the expression above reduces to:

$$\frac{\partial P_j}{\partial x_k} = P_j\, \beta_j - P_j \sum_{j=1}^{J} P_j\, \beta_j$$

Elasticity now becomes

$$E_k^{P_j} = (\beta_i - \sum_{j=1}^{J} P_j\, \beta_j)\, x_k$$

Elasticities reported in table (5.2) are based on this formula.

---

1. In the presence of an interaction term, between say, variable x_k and variable x_{k+1}, the elasticity formula is simply $P_j\, x_{jk}\, (\beta_{jk} + \beta_{jk+1}\, x_{k+1})\, (1 - P_j)$

Appendix B: Selectivity bias in the Demand for Health Care

Since persons who had not reported an illness or an injury during the relevant period were excluded from the estimating sample, we suspected that the parameters of the dichotomous demand equations might be subject to sample selection bias. For this reason a Probit demand equation may be estimated using an algorithm due to van der Ven and van der Praag (1981), an extension of Heckman's (1976, 1979) selectivity bias correction. We have opted instead for a maximum likelihood procedure involving two probit equations. Before reporting the results, it will be useful to outline these procedure in the context of this analysis.

Two Step Procedure

We begin with a random sample of I observations. Equations for individual i are:

$$(1)\ Y_{1i} = \beta_1' X_{1i} + u_{1i}$$

$$(2)\ Y_{2i} = \beta_2' X_{2i} + u_{2i}$$

In our case, equation (1) is the medical care equation (for the moment we leave aside the equation which dependent variable is used). In equation (2) the dependent variable is the probability of having an illness or injury.

Equation (2) may be estimated over the entire sample. On the other hand, Y_{1i} is known only for those individuals with positive sick time. Put differently, the value of Y_{1i} is known if $Y_{2i} > 0$, or using (2), if $u_{2i} > -\beta_2' X_2$. If the subsample used to estimate equation 1 is selected in a non-random fashion, than our estimates will be biased. Formally, the population regression function of equation (1) is written.

$$E(Y_{1i}|X_{1i}) = \beta_1' X_{1i}$$

The regression of the subsample depends not only on the vec or of exogenous variable X_{1i}, but also on the sample selection rule, that is

$$E(Y_{1i}|X_{1i}, Y_{2i} > 0) = \beta_1 X_{1i} + E(u_{1i}| u_{2i} > -\beta_{2i} X_2)$$

The bias arises from the omission of the last term on the right hand side from the estimating equation.

By assuming that u_{1i} and u_{2i} are jointly and normally distributed, Heckman was able to redefine the selection rule in the following manner: [1].

$$E(u_{1i}|u_{2i} > -\beta_2' X_{2i}) = \frac{\sigma_{12}}{(\sigma_{22})^{1/2}} \lambda_i$$

where

σ_{ij} are variance-covariance terms of u_1 and u_2.

---

1. Also see Johnson and Kotz (1972) pp. 112-113.

λ_i . is the inverse Mill's ratio, related to the probability of being included in the subsample. [1]

Since most computer programs make the normalizing assumption that

$\sigma_{11} = 1$, we may state the following:

(3) $Y_{1i} = \beta_1' X_{1i} + \rho\lambda_i + e_{1i}$

noting that

ρ is the correlation coefficient $(\rho = \frac{\sigma_{12}}{\sigma_{11}^{1/2}\ \sigma_{22}^{1/2}})$ and

e_{1i} is the error term of the "corrected" subsample regression.

---

1. $\lambda_i = \frac{\phi\ (-\beta_1' X_{2i})}{\Phi\ (\beta_1' X_{2i})}$

where $\phi(.)$ and $\Phi(.)$ are, respectively the density function and cumulative distribution function of a standardized normal random variable. Note that if the selection rule is defined as a probability then:

$P(u_{2i} > - \beta_2' X_{2i}) = F(\beta_2' X_{2i})$

where F (.) is the c.d.f. of a normal random variable. Clearly, λ_i is a monotone <u>decreasing</u> function of the probability that an observation is included in the sample.

As we have just shown, in order to generate λ, the elements in the X_{1i} vector must be normally distributed. For this reason equation (2) is estimated as a Probit. If, in equation (1), we had a continuous dependent variable, say, number of visits to a health worker, then we would be able to estimate equation (3) using OLS and stop there.

In our case however, the demand equation of interest explains the probability of obtaining medical during the relevant period. We do not observe this probability, but rather a limited dependent variable such that

$Y_{1i} = 1$ If an individual obtained medical care.

$Y_{1i} = 0$ If an individual did not obtain medical care.

Van der Ven and van Praag suggest estimating this dichotomous equation as a PROBIT. In order to take account of selectivity bias they estimate a modified version of equation (3).

$$(3')\quad Y_{1i} = 0 \quad \text{if} \quad \beta'(X_i/V) + \rho(\lambda_i/V) + \varepsilon_i \leq 0$$
$$Y_{1i} = 1 \quad \text{if} \quad \beta'(X_i/V) + \rho(\lambda_i/V) + \varepsilon_i > 0$$

V is the variance of the error term obtained from the linear probability regression of equation (3), that is $V = \Sigma\,(e^2)$. For a derivation of V, see Heckman (1979), pp 156-157.

This procedure is only an approximation of the Heckman correction for the case of a standardized normal random variable.

However, van de Ven et al have shown that it yields essentially the same coefficients as the maximum likelihood estimation.

Maximum Likelihood Estimation

The maximum likelihood function is given by:

$$L = \prod_{i=1}^{n_1} \Phi_1(\alpha' x_i, \beta' Z_i; \rho) \prod_{i=n+1}^{n} \Phi_2(-\alpha' x_i, \beta' Z_i; -\rho) \prod_{i=1}^{m} \Phi(-\beta_i' Z)$$

The first multiplicative term refers to N_1 persons with illness or injury who consulted a health practitioner ($Y_{2i} = 1$, $Y_{1i} = 1$), the second term refers to persons with illness or injury who consulted no one ($Y_{2i} = 1$, $Y_{1i} = 0$), while the third term represents individuals with no illness ($Y_{2i} = 0$).

The model distinguishes between traits that are relevant over the entire sample (a vector Z), and traits that are specific to persons with positive sick time (a vector X). Thus Φ_1 and Φ_2 each represent a bivariate, normal c.d.f. which generates ρ ,the correlation coefficient of the random variables $\alpha' X_i$ and $\beta' Z_i$.[1]

Table B.1 shows results of the MLE procedure for the probability of being ill during the past four weeks and the probability of subsequently seeking medical care. Note that in our case the X vector contains only one variable i.e, the number of unrestricted activity days reported by the individual (ADAY). The Z-vector contains

---

1. For a normal definition of the bivariate normal distribution and a discussion of its properties see Johnson and Kotz, pp. 93-95.

the common demographic or socioeconomic characteristics as well as access to health care measured by travel time to available sources of care. The demand equation may be compared directly with similar logit and probit regressions in Table 5.1, which ignores selectivity bias. It is immediately obvious that the marginal effects of each independent variable on the probability of seeking care, are very similar in both the uncorrected and corrected models. Furthermore, the coefficients of the Probit regression ignoring selectivity bias were virtually identical to the results of the corrected Probit, and were substantially more significant. The same is true for the health equation (the uncorrected health regression is not shown in the paper. It turns out that selectivity bias does not arise here, implying that the incidence of illness or injury is random in the population. This randomness is also reflected in the negligible value of the correlation coefficient of the errors obtained from the probabilistic demand and health equations ($\rho = -.002$).

Table B.1: Selectivity Bias
Rural Adults (Probit)

	Probability of Illness or Injury (ILL)			Probability of Seeking Care (CON)		
	β	T	Slope	β	T	Slope
CONSTANT	-1.067	(11.17)	-.392	1.394	(.25)	.556
AGE	.019	(10.50)	.007	-.018	(.38)	-.007
MALE	-.010	(.15)	-.004	.104	(.95)	.042
EDUC	.352	(.27)	.001	-.031	(1.30)	-.013
EXP (10^6)	.040	(1.30)	.015	.131	(1.10)	.052
SIZE	-.012	(3.59)	.005	-.007	(.21)	-.003
TIMNURS	.067	(1.42)	.025	-.312	(1.66)	-.124
TIMTRAD	.029	(.31)	.011	.274	(.52)	.109
ADAY	-	-		-.029	(5.37)	-.012
ρ			-.002	(0.05)		
Log Likelihood			1749.9			
X^2			244.10			

REFERENCES

Acton, J.P., 1975, "Nonmonetary Factors in the Demand for Medical Services: Some Empirical Evidence" Journal of Political Economy 83, 595-614.

Acton, J.P. "Demand for Health Care Among the Rural Poor, with Special Emphasis on the Role of Time". In Richard N. Rosett The Role of Health Insurance in the Health Services Sector. New York: National Bureau of Economic Research 1976.

Ainsworth, Martha. "User Charges for Cost Recovery in the Social Sectors: Current Practices "Mimeo World Bank, August 1983.

Akin, John S, Griffin, Charles C., Guilkey David, K. Popkin, Barry M. The Demand for Primary Health Services. In the Third World. Totowa, New Jersey: Romand and Allanheld (1985).

Akin, John S., Guilkey, David K. and Popkin, Barry M. "The Demand for Child Health Services in the Philippines" Social Science and Medicine 15c (1981): 249-257.

Amemiya, Takeshi "Qualitative Response Models: A Survey" Journal of Economic Literature 1981 (483-536)

Andersen, Roland and Benham, Lee, Factors Affecting the Relationship between Family Income and Medical Consumption, in: H. Klarman ed., Empirical Studies in Health Economics, Baltimore, MD: Johns Hopkins University Press, 1970.

Andersen, Roland, Kravits, Joanna and Anderson, Odin W., 1975, Equity in Health Services: Empirical Analyses in Social Policy; Cambridge, MA: Bellinger (1975).

Bartel, Ann and Taubman, Paul. "Health and Labor Market Success: The Role of Various Diseases" The Review of Economics and Statistics 61 (1979): 1-8.

Becker, Gary s. "A Theory of the Allocation of time." Economic Journal 75 (September 1965): 493-517

Ben-Akiva, Moshe and Lerman, Paul. Discrete Choice: Theory and Applications to Travel Demand. Cambridge, MA: MIT Press, 1985

Benham, L. and Benham, A., Utilization of Physician Services across Income Groups, 1963-1970, in: Andersen et al 1975.

Berkowitz, Monroe, Fenn Paul Lambrinos, James "The Optional Stock of Health with Endogenous Wages" Journal of Health Economics 2 (August 1983); 139-148.

Birdsall, Nancy and Chuhan Punam. Willingness to Pay for Health and Water in Rural Mali: Do WTP questions work?". Mimeo World Bank, February 1983.

Coffey, Rosanna M. "The Effect of Time Price on the Demand for Medical Care Services", Journal of Human Resources 18 (Summer 1983): 407-424.

Colle, Ann D. and Grossman, Michael. "Determinants of Pediatric Care Utilization." Journal of Human Resources 13 (Supplement 1978): 115-58.

Cooper, Barbara S. and Rice, Dorothy P. "The Economic Cost of Illness, Revisited" Social Security Bulletin 39 (1976) 21-36.

de Ferranti, David. "Paying for Health Services in Developing Countries: An Overview. World Bank Staff Working Papers No. 721 (1985).

Edwards, Linda N. and Grossman, Michael. The Relationship between Children's Health and Intellectual Development. In: Selma Mushkin, ed. Health: What is Health Worth? New York: Pergamon Press 1979.

Goldman, Fred and Grossman, Michael. "The Demand for Pediatric Care: An Hedonic Approach." Journal of Political Economy 86, 2:1 (April 1978): 259-80.

Colladay, Fredrick. "Health Problems and Policies in the Developing Countries" World Bank Staff Working Papers No. 412 (August 1980).

Grootaert, Christian. An Annotated Questionnaire to Measure Levels of Living. LSMS Staff Working Paper No. 24. The World Bank, 1986.

Grossman, Michael. The Demand for Health: A Theoretical and Empirical Investigation. Occasional Paper 119. New York: National Bureau of Economic Research, dist. by Columbia University Press, 1972.a

Grossman, Michael. "On the Concept of Health Capital and the Demand for Health" Journal of Political Economy 80 (1972b): 223-255

Grossman, Michael and Benham Lee. "Health, Hours and Wages" in: Mark Perlman, ed. The Economics of Health and Medical Care London: MacMillan and Co. 1974.

Grossman, Michael. "The Correlation between Health and Schooling" In: Nestor E. Terleckyj, Household Production and Consumption, National Bureau of Economic Research, 1975.

Hausman, Jerry A. and Wise, David A. "A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Hetergeneous Preferences" Econometrica 46:2 (March, 1978): 403-426

Heller, Peter S. "A Model of the Demand for Medical and Health Services in Peninsular Malaysia" Social Science and Medicine 16 (1982): 267-284.

Hershey, John C., Luft, H., Harold S. and Gianaris, Jean M. "Making Sense Out of Utilization Data." Medical Care 13 (October 1975): 838-54.

Holtmann, A.G. and Olsen Jr., E. Odgers. The Economics of the Private Demand for Outpatient Health Care. DHEW Pub. (NIH) 78-1262. Washington: U.S. Government Printing Office, 1978.

Johnson, Norman L. and Kotz, Samuel. Distribution in Statistics: Continuous Multivariate Distributions. John Willey and Sons (1972)

Luft, H. "The Impact of Poor Health on Earning" Review of Economics and Statistics 57 (1976): 43-57.

McFadden, Daniel. "Qualitative Response Models". In W. Hildenbrand ed. "Advances in Econometrics: invited papers for the Fourth World Congress of the Econometric Society". Cambridge: Cambridge University Press, 1982

McFadden, Daniel. "Econometric Models of Probalistic Choice". In C. Manksi and D. McFadden, eds., Structural Analysis of discrete Data with Econometric Applications. Cambridge MA: MIT PRESS (1981)

McFadden, Daniel. "Conditional Logit Analysis of Qualitative Choice Behavior", In P. Zarembka ed., Frontiers in Econometrics, New York: Academic (1973)

Mwabu, Germano M. "Conditional Logit Analysis of Household Choice of Medical Treatments in Rural Villages in Kenya" forthcoming in Economic Development and Cultural Change.

Musgrove, Philip, "Family Health Care Spending in Latin America". Journal of Health Economics, 2:3 (December 1983): p 245-258.

Small, Kenneth A. and Rosen, Harvey S. "Applied Welfare Economics with Discrete Choice Models" Econometrica 49:1 January, 1981)

Phelps, Charles E. "Effects of Insurance on Demand for Medical Care." In Equity in Health Services: Empirical Analyses in Social Policy, Andersen et al, 1975.

Maddala. G.S. Limited-Dependent and Qualitative Variables in Econometrics Cambridge: Cambridge University Press, 1983.

Phelps, Charles E. and Newhouse, Joseph P. "Coinsurance, the Price of Time, and the Demand for Medical Services." Review of Economics and Statistics 56 (August 1974): 334-42.

Preston, Samuel A. "The Changing Relationship between Mortality and Level of Economic Development" Population Studies 29:2, 1975; 231-248.

Preston, Samuel A. "Causes and Consequences of Mortality in Less Developed Countries" in: R. Easterlin, ed. Population and Economic Charge in Developing Countries, New York: National Bureau of Economic Research, New York 1980.

Salkever, David S. "The Problem of Access to Medical Care: A Consumer Demand Analysis." Eastern Economic Journal 2 Supp. (July 1975): 116-131.

Salkever, David S. "Accessibility and the Demand for Preventive Care." Social Science and Medicine 10 (September-October 1976): 469-75.

Van der Gaag, Jacques, and Lee, Myung. Consumption and Distribution of Welfare in The Ivory Coast. Mimeo, The World Bank 1984.

Van der Gaag, Jacques. The Health Care Sector in The Ivory Coast. Mimeo. The World Bank, 1985.

Van der Ven, Wynand P.M.M. and van der Gaag, Jacques. "Health as an Unobservable: A MIMIC-Model of Demand for Health Care" Journal of Health Economics 1:2 (August 1982): 117-215.

Varian, Hal R., Microeconomic Analysis. New York: W. W. Norton and Company, 1984.

Wilks, S.S. Mathematical Statistics. New York: John Wiley and Sons (1962)

World Bank WORLD DEVELOPMENT REPORT 1984. Oxford University Press (July 1984).