How Poverty Affects the Health Status and the Health Care Demand Behaviour of Households? The Case of Rural Ethiopia

Abay Asfaw
Centre for Development Reseaarch (ZEF)
University of Bonn
Walter Flex Str. 3 D-53113 Bonn, Germany
e-mail: a.asfaw@uni-bonn.de

Abstract:

The paper examines the impact of poverty on the health status, entry into the health care market, and the provider choice decision of rural households of Ethiopia. It also investigates the demand diversion and reduction effects of user fees on the chronically poor households. The results show that the poor are more likely to fall ill but less likely to get out side medical help. Poverty not only directly affects the health status of individuals but also increases the duration of illness and hampers the cross effects of education on reducing the incidence of illness and the probability of seeking outside medical help. The results also reveal that compared to other family members immediate family members are more likely to report illness, to get treatment, and to visit modern health care providers. The results of the nested multinomial logit results also show that an increase in user fees is likely to drive out a significant portion of the poorest households and the socially disadvantaged individuals within households from the health care market, which will aggravate the existing inequality in access to basic health care services.

1. INTRODUCTION

Analysing the health care demand behaviour of households has paramount importance in identifying the socially excluded group of the population and the deprived individuals within households from the health care market. It also helps to predict the impact of various health related policy issues such as cost recovery measures on the health care demand behaviour of the poorest segment of the population. This paper has three interrelated objectives. First, it tries to identify the most venerable group of the population and individuals within a family to health shocks by examining the determinants of health status of individuals in the rural areas of Ethiopia. Second, it investigates who gets medical help and why by thoroughly analysing factors that affect the decision of households to seek medical help given illness/injury. Finally, it examines the impact of poverty on the health status, health care demand behaviour, and provider choice of rural households and the probable consequences of increasing user fees on the poorest segment of the population. The data collected by the Centre for Development Research (ZEF) at the University of Bonn in rural areas of Ethiopia is used for the analysis. The data were collected from four regions (namely Amhara, Dire Dawa, Oromiya, and Southern Nations, Nationalities and Peoples (SNNP)) of the country. Over all, 550 households (with a total of 2805 members) were selected based on a three stage sampling procedure from seven villages or peasant associations (PAs). The data were collected by trained enumerators using well-designed questionnaire.

2. IMPACT OF POVERTY ON HEALTH STATUS AND ENTRY INTO THE HEALTH CARE MARKET

2.1. Descriptive Analysis

In this section, a descriptive statistics is used to analyse the interaction between poverty and the incidence of illness, its duration, and the decision to seek outside medical help by those individuals with a perceived health problem. It is also tried to investigate the impact of poverty on health care provider choice of households. Poverty is approximated by income and those households in the lower quartile of the income distribution are considered as chronically poor. Incidence of illness is measured by self-reported symptoms during the last 12 months before the survey and duration of illness is approximated by the number of days adult members of the household unable to work. Table 1, Figures 1, and 2 portray the relationship between poverty (including various demographic variables) and the incidence and duration of illness and the decision to enter into the health care market.

Table 1 shows that among the sampled 2805 individuals[1], 31 percent reported illness or injury in the last 12 months before the survey and 4.3 percent suffered from disability. Various factors may explain differences in the frequency of self-perception of illness. Similar to the findings of other studies in Ethiopia and neighbouring countries (CSAE 1997, Frederickx 1998), illness incidence is a bit higher for females than males. If we see the differences across age groups, females of childbearing age (15–45) are more susceptible to illness (33.3 %) probably due to their obstetrical needs than their male counterparts (29.3%) though this difference is not statistically significant (p = 0.659 analysis of variance). Generally, as age increases the tendency of individuals to fall ill and suffer from disability increases irrespective of sex.

If we disaggregate the incidence of illness and disability by income quartile, about four in ten individuals are reportedly ill in the poorest quartile compared to two in ten in the richest quartile. At the same time, the disability problem in the poorest quartile is more than double of the problem in the richest quartile. This shows that the hypothesis that rich households perceive health problems more often than poor households does not hold in our data set. The duration of illness measured by the number of individuals (age greater than 6) unable to work the usual activities also follows more or less similar pattern to disability and incidence of illness. Duration of illness increases as age increases and it decreases as education and income increase. The mean duration of illness for households with illiterate head is 49 days per ill person per year and 31 days for literate head households and the difference is statistically significant (p = 0.002 analysis of variance). The difference is much higher and more significant in the case mothers' education. Poverty has very significant role in determining the duration of illness. The mean duration of illness for the poorest quartile is 1.6 times higher than the richest quartile and the difference across all income groups is statistically significant (p = 0.092 analysis of variance). CSAE (1997: 5) also reported "Controlling for other characteristics, the illnesses of the poorest fifth of rural households last about 25% longer than those of the richest fifth". Probably this can be due to the fact that more educated and relatively wealthy households are better informed, sensitive to illness and have the capacity to send their ill members to health care provider before the illness get worse.

As it is the case in most developing countries, in the rural areas of Ethiopia, illness does not necessarily lead to demand for medical care owing to various reasons. First, some individuals who reported illness may not think that they need medical help. Second, even those individuals who perceived health problem and the need for medical help might not be able to translate their need into effective demand. As a result, there is a wide variation between perceived illness and actual demand for health care. Out of the 831 individuals who reported illness or injury, quarter of them do not seek any type of outside medical help[2].

[1] Since information was gathered about every individual living in the household at the time of the survey, the total sample size is around 2805 individuals.

[2] This figure seems low compared to 4 weeks recall period results of 45.5 % for Ethiopia (CSAE 1997) & 33.9 % for Kenya (Frederickx 1998) but comparable with 12 months recall period result (33.3%) of CSA (1999) for Ethiopia. Possible reason for this may be individuals usually remember and report only treated illness episodes.

Table 1 Cross Tabulation of Demographic and Economic variables and Health Indicators

Demographic and Economic variables			Incidence of Illness (% of people reported illness)	Disability (% of people reported disability)	Duration of illness (Mean no of days unable to work)*	Seek medical care (% of people sought any medical help given illness)
Total			31.0	4.3	40.9	76.5
Gender and Age	Female		31.4	4.4	42.3	76.8
	Male		30.6	4.3	39.5	76.2
	Female	Age < 15	27.0	1.9	51.7	76.0
		Age (15 – 45)	33.3	5.9	33.3	77.7
		Age > 45	43.0	7.2	76.6	76.3
	Male	Age < 15	26.9	2.5	25.8	79.4
		Age (15 - 45)	29.3	4.1	39.4	72.8
		Age > 45	49.4	9.4	63.0	77.1
	Total	Age < 15	26.9	2.2	29.1	77.7
		Age (15 - 45)	31.3	5.0	38.9	75.4
		Age > 45	46.8	8.5	64.8	76.8
Education	Mother cannot read and write		31.9	5.0	46.1	72.6
	Mother can read and write		28.5	2.6	24.2	87.9
	Head cannot read and write		30.2	5.3	49.2	70.3
	Head can read and write		31.6	3.6	30.9	81.2
	Highest grade completed by the head	Illiterate	29.7	5.3	46.7	71
		1 – 3 grade	37.3	3.1	39.6	79.2
		4 – 6 grade	32.3	2.4	33.5	81.1
		> 6 grade	23.5	5.5	32.5	83.5
Income	Poorest quartile		43.5	8.8	44.7	71.6
	Poorest higher quartile		29.4	4.5	48.6	79.0
	Higher middle quartile		28.2	2.5	36.4	75.8
	Riches quartile		23.3	3.2	28.2	82.5
Illiterate mother	Poorest quartile				43.3	69.0
	Richest quartile				24.67	74.3
Literate mother	Poorest quartile				51.61	78.2
	Richest quartile				23.43	93.4

* Only for household members reported illness or injury and aged > 6

Figure 1. Relationship between Income and Various Health Indicators

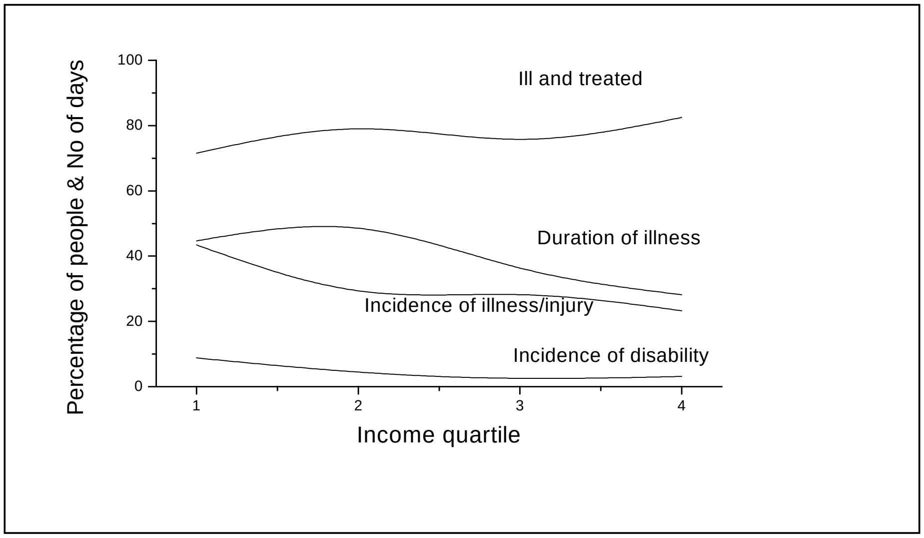
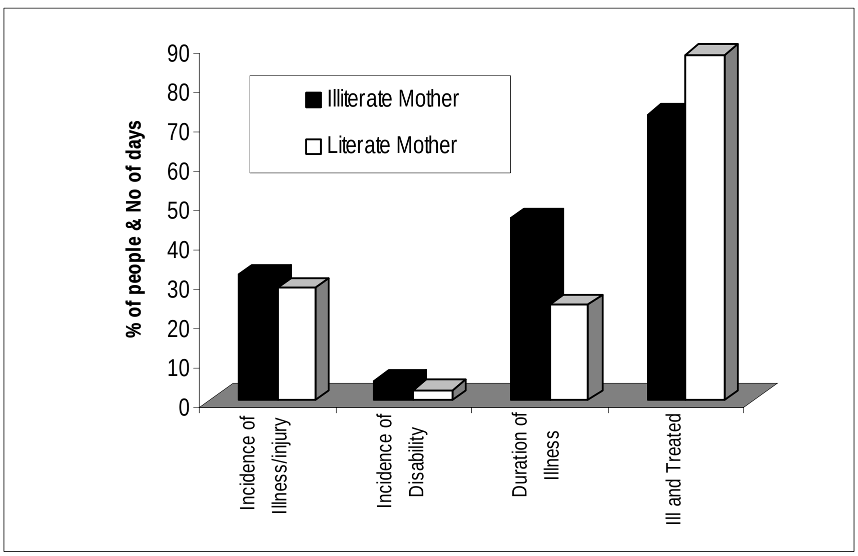


Figure 2. Relationship between Mothers' Education and Various Health Indicators

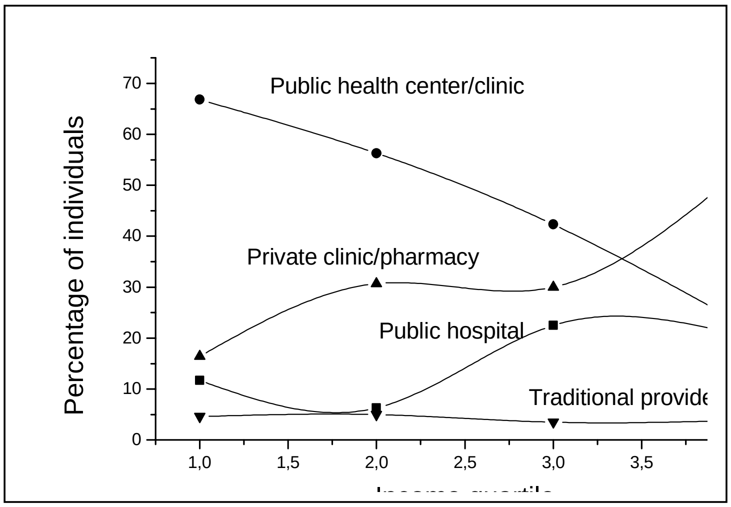


There are significant differences in the propensity to seek medical care across individual and household characteristics. The last column of Table 1 portrays that among those perceiving a health problem, educated and wealthy households are more likely to seek care than illiterate and poor households. For instance if the head of the household can read and write eight out of ten ill individuals are likely to get treatment compared to seven out of ten if the head is illiterate. The difference is more significant in the case of mothers' education.

There are no statistically significant gender and age differences in seeking medical care among sampled households. This is also true for Ethiopia (CSAE 1997), Kenya (Mwabu et al. 1993) and Tanzania (Frederickx 1998). Generally, as Figure 1 and 2 clearly demonstrate the incidence of illness/injury, disability, and duration of illness decrease and the probability of seeking treatment given illness increases with income and education.

It is also tried to see the desire and the actual patterns of provider choice. In the sampled areas, health services are delivered by the government (public hospitals, health centres, and clinics), the private sector (private clinics, pharmacies, and home of health workers), non-governmental organisations (NGO clinics), and by the traditional providers (holly water and traditional practitioners). As it is the case in most developing countries, the public health care providers are subsidized and staffed with qualified personnel (albeit less motivated) and the private and the NGO clinics are better stocked in drugs though very expensive.

Figure .3 Income & Provider Choice



Significant differences can be observed in the utilization of providers across different income groups. As Figure 3 clearly shows, relatively wealthy households tend to opt private providers and public hospitals while the level of utilization of traditional providers (especially of Holly water) remains more or less the same.

2.2. Econometric Analysis

Self-reported symptom is used as an indicator of health status since other indicators such as inability indices and the number of days individuals are unable to work do not take into account the health status of children[3]. Except duration of illness, which is measured in a continuous fashion, both 'incidence of illness or injury' and 'incidence of seeking medical care' are measured as dummy variables. Therefore, any dichotomous model can be used

[3] BMI cannot also be used since data on height and weight of individuals were not collected.

to analyse factors that determine the probability of falling ill and of seeking medical care. If we use a probit model, the probability of an individual *i* in household *j* will fall sick or will get medical care (P_{ji}) can be written as

$$\mathrm{P}_{\mathrm{ji}} = \mathrm{Prob}(\mathrm{Y}_{\mathrm{ji}} = 1) = \Phi(-\beta' X) = \int_{-\infty}^{\beta' X_{ji}} \frac{1}{(2\Pi)^{1/2}} e^{(\frac{-t^2}{2})} dt \qquad (1)$$

Where

X_{ji} is a vector of individual specific characteristics (such as age, sex, severity of illness, education, etc.) and household level variables (such as income, educational level of the household head, distance of households form health providers, religion, etc.), t is a standardised normal variable with mean 0 and variance 1 and βs are parameters to be estimated.

Theoretically, various factors ranging from individual specific to family and village level characteristics can affect the incidence of illness and the propensity to seek medical care. Variables such as age, sex, vaccination history, and relation to the head are taken as individual characteristics and factors such as religion, ethnicity, income, literacy of the head and the mother, availability of latrine and separate room for animals, distance to the nearest health care provider are taken as household level variables to explain incidence of illness and treatment. Since illness may also affect the income of households, income can be endogenous to the system. Therefore, the self-evaluation of wealth status as poor, medium, and rich is used as an instrumental variable to income. Table 2 presents the probit model results with income instrumented by self-evaluation wealth status. For the sake of robustness, the OLS and maximum likelihood results of the original specification (without using wealth as an instrument for income) are also given in Appendix 1. Since the F test cannot be used to test the overall fitness in a discrete choice model, the chi-square statistics of the following form is used.

$$\chi_{(n)}{}^{2} = -2\ln\frac{L_R}{L_U} = -2(\ln L_{R-} \ln L_U) \qquad (2)$$

Where L_R and L_U are the restricted and the unrestricted likelihood results respectively.

The chi-square result shows that we can reject the restricted model in favour of the model with all the explanatory variables at less than one percent level of significance for both specifications. There is no significant difference in our results when income is considered as endogenous and instrumented by self-evaluation of wealth (Table 2) and when it is taken as exogenous variable (Appendix 1). Some interesting patterns emerge from Table 2.

In line with our descriptive analysis, there is no significant gender and age bias in probability of falling ill and seeking medical help in the sampled areas. This result is similar to the findings of Frederickx (1998) for Tanzania. Literacy of the head is positively associated with reporting illness probably indicating that educated households have better awareness about health and illness. Literacy of he head and the wife is positively associated with seeking medical care and the latter is highly significant. Specifically the result shows that the probability of ill individuals to get medical help, computed at mean values of all explanatory variables, increases by 21.68 percent if the mother in the household can read and write. A related study conducted in Ethiopia (CSAE 1997) presented similar results. According to this study, having an educated mother (completed primary education) is likely to increase the probability of seeking treatment by 25 percent. This is in line with the arguments of most scholars that females' education is one of the effective ways to improve the health status of households.[4]

However, the impact of mothers' education on the decision to seek medical care pays off mainly for the middle and higher income groups. The descriptive analysis shows that out of the total individuals reported illness in the non-poor and literate mother households, 93.4 percent seek medical help compared to 78.2 percent in the poor and literate mother households (Table 1). This is also confirmed by the regression analysis results. Evaluating all other covariates at their mean value, the impact of mothers' education on increasing the probability of seeking medical care given illness is only 4 percent (0.2168 - 0.1760) for poorest households while it is nearly 40 percent (0.2168 + 0.1760) for non-poor households. Frederickx (1998) also finds similar results for Tanzania in the case of incidence of illness. However, our results do not support his argument that female education may not have positive cross-effect on health outcomes of households since our result shows that literate mothers have better performance even within poor households. For instance, the percentage of individuals who seeks medical care in poor and literate mother households is 13.3 percent higher than the individuals in the poor and illiterate mother households (Table 1). If we also take the impact of all other covariates into account, being member of a poor household and having illiterate mother is likely to reduce the probability of seeking medical help (given illness) by 17.6 percent.

The other important factor that affects the health status of individuals is the preventive measures taken by households. Around the mean, having latrine decreases the probability of reporting illness by 14.1 percent and putting animals in a separate room by 6.8 percent. Vaccination has also a statistically significant impact on reducing the probability of reporting illness though its effect is significant only for children as shown by the positive and significant age and vaccination interaction variable.

These results demonstrate that the incidence of illness can be reduced if rural households are thought and encouraged at least to use latrines and to take their children to vaccination centres where they can usually get free or highly subsidized vaccinations for most of the deadly diseases. Table 2 also shows that the probability of seeking medical help declines with distance. A one-hour decline in the distance to the nearest health care provider would increase the probability of seeking medial care by 0.6 percentage point. This is also consistent to the finding of CSAE (1997) for rural Ethiopia.[5]

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[4] An attempt is also made to explore factors that affect duration of illness. The results show that mothers' education and income of the household have a statistically strong impact in reducing the duration of illness.

[5] They found that moving clinics 1 km closer to households would increase the incidence of seeking treatment by 1 percent.

Table 2. Binomial Probit Model: Determinants of Incidence of Illness and Treatment

Variables	1 if the individual reports illness or injury and 0 otherwise		1 if the individual Seeks medical care and 0 otherwise	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Sex (1 if female)	0.0357 *(0.0519)*		0.0458 (0.1003)	
Age	0.0069 (0.0055)		-0.0017 (0.0089)	
Age square	0.0000 (0.0000)		0.0000 (0.0001)	
Vaccination (1 if vaccinated once in life)	-0.3532* (0.1215)	-0.1232* (0.0424)		
Vaccination * Age	0.0983*** (0.0033)	0.0343*** (0.0194)		
Literacy of the head (1 if the head can read and write)	0.1872* (0.0607)	0.0653* (0.0212)	0.1232 (0.1169)	
Literacy of mother (1 if the mother can read and write)	-0.0719 (0.0677)		0.7264* (0.1977)	0.2168* (0.0579)
Literacy of mothers * poor (1 if the household income is in the lowest quartile)			-0.5897** (0.2674)	-0.1760** (0.0792)
Family Size	0.0047 (0.0108)		0.0169 (0.0244)	
Self evaluated wealth status (1= poor, 2 = medium, and 3 = rich)	-0.1372* (0.0482)	-0.0479* (0.0168)		
Log income			0.0715*** (0.0408)	0.0213*** (0.0122)
Relation to the head (1 for self, wife and children and 0 otherwise)	0.3173* (0.0909)	0.1176* (0.0317)	0.4862* (0.1909)	0.1451* (0.0568)
Latrine (1 if the household has latrine)	-0.4037* (0.0711)	-0.1408* (0.0247)		
Share room with animal (1 if the family shares room with animals)	0.1961* (0.0544)	0.0684* (0.0189)		
Sex of the head (1 if female)			-0.0174 (0.1605)	
Age of the head			-0.0525*** (0.0282)	-0.0157*** (0.0084)
Age square of the head			0.0005*** (0.0003)	0.0001*** (0.0000)
Distance (Distance of the house from the nearest health care provider in hours)			-0.0224*** (0.0144)	-0.0067*** (0.0044)
Constant	-0.6312* (0.1889)		0.8691 (0.7161)	
No of observations	2690		828	
Log likelihood function	-1588.373		-420.3228	
Restricted log likelihood	-1670.229		-451.9602	
Chi – squared	163.712*		63.2748*	

Figures in parenthesis are standard errors.
* Significant at 1 and less than 1% confidence level
** Significant at 5 and less than 5 % confidence level
*** Significant at 10 and less than 10% confidence level

In spite of the fact that rich households report less illness, they are more likely to get medical help. Keeping all other factors at their mean value, a 1 percent rise in income of households increases the probability of seeking medical help by 2.13 percent indicating that poor households are more likely to fall ill but less likely to get medical care. This implies that the poor have not been benefiting from the existing government subsidies in public health care providers. There is also statistically significant evidence that the health problem of immediate family members (head, spouse, and children) is highly recognized and treated compared to other non-immediate members including hired family members. The result shows that the probability of reporting illness for immediate family members is 11 % higher than the non- immediate family members. The discrimination is much higher in the case of seeking medical help. Given illness or injury, ceteris paribus, the probability of getting medical help for non-immediate members is 14.5 percent less than the probability of getting medical help for immediate members. This implies that in the sampled households relation to the head is an important factor in both perceiving and finding solutions for health problems rather than gender and age differences.

To conclude this section, there is no statistically significant gender and age discrimination in reporting and seeking medical care in the sampled households.[6] Variables related to prevention are highly significant revealing that measures such as vaccination, using latrine and having a separate room for animals have a paramount importance in reducing incidence of illness compared to any other variables. Evaluating all other variables at their mean value, a combined effect of the above three preventive measures is likely to reduce the incidence of illness by one third. This is an interesting finding since all the preventive measures (probably except having a separate room for animals) can be done without putting additional financial pressure both on households and the government. Education level of mothers, income, and the relation of individual members to the head of the household are the most decisive factors in determining the chance of getting medical help. However, the impact of mothers' education on increasing demand for medical care is trimmed down by poverty. The cross effect of mothers' education on the decision to join the health care market is 10 times less in the poorest households than in the non-poor households. Poverty not only hampers the cross effect of education on health but also directly influence the health status of households. Poor individuals fall ill more often, yet seek medical help less frequently than rich households.

This analysis, however, does not allow us to make inference and predictions about the impact of poverty on the demand for medical care and does not permit us to assess the influence of health related policy measures such as increasing user fees on the poorest of the poor. Based on a standard random utility maximization theory and a discrete choice model, the next section addresses these issues.

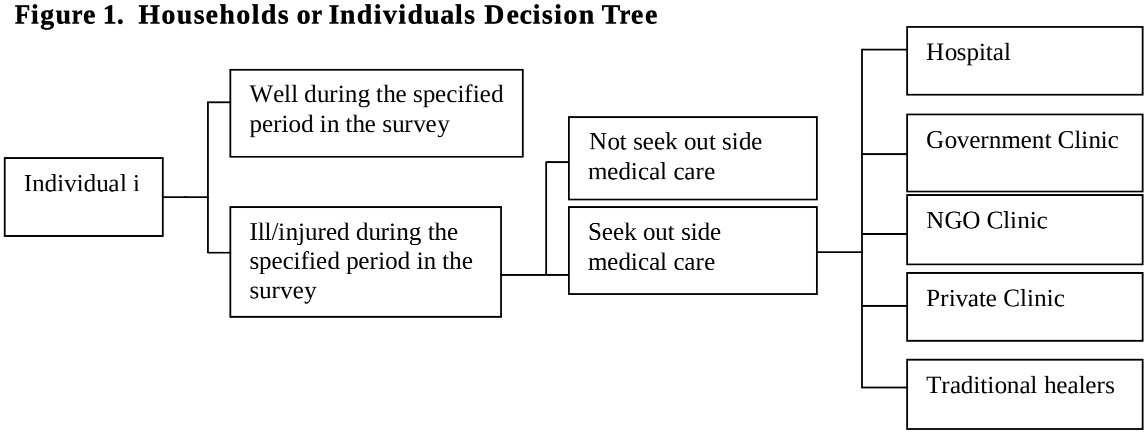
[6] We have also tried to see if there is any pattern across different ethnic and religious groups. The result (not presented) shows that religion and ethnicity do not have statistically significant impact both on the probability of falling ill and entering into the health care market though the Oromos tend to seek more medical help.

3. Poverty and the Health Care Demand Behaviour of Households

3.1. Analytical frame work

The modern health care demand analysis is heavily based on the neo-classical paradigm of rational consumer and constrained utility maximisation theories. The basic idea in most of the health care demand analysis is that an individual that faces different health care providers is assumed to maximise utility from health (H) and consumption of a composite good (C) subject to income and health production function constraints. This implies that in an event of illness or injury individuals or the household must decide whether to seek medical care and from which provider based on price and non-price factors and the perceived quality of the provider. Then individuals will choose among an array of providers the alternative that gives them the maximum utility. If we assume that provider j yields the greatest utility to individual i then the probability that the j^{th} alternative will be chosen (given the individual seek medical care) is taken as the health care demand function for individual i. Diagrammatically, the procedure can be presented as shown in Figure 1.

Figure 1. Households or Individuals Decision Tree



The problem can also be presented algebraically as follows. A sick/injured rural individual *i* that faces *J+1* treatment options, the *J+1th* alternative being self-care (no outside care), in a given period is assumed to maximise a utility function conditional on obtaining treatment from provider j (U_{ij}) given by:

$$\text{Max: } U_{ij} = U(H_{ij}, C_{ij}) \quad (3)$$

Subject to:

$$Y_i = P_{ij} + pc\, C_{ij} \;\; \text{(Budget constraint)} \quad (4)$$

$$H_{ij} = H0 + Q_j(X,Z) \quad \text{(Health production function)} \quad (5)$$

Where

H_{ij} is the post-treatment health status of the individual who gets treatment form provider j,

C_{ij} is the consumption level after health care provider j is chosen and pc is its price, which is normalised to one for identification purpose,

Y is the total income of the individual or the household,

P_{ij} is the direct cash payment, transport cost, and the opportunity cost of time to get treatment from provider j,

H0 is the initial health status of the individual, and

Q_j is the health improvement from provider j, which is a function of a vector of individual characteristic (X) that affect health outcome and a vector of provider characteristic (Z).

Then, the problem of the individual is to maximise the unconditional utility function (U*) given by

$$U_i^* = \text{Max}\,(U_{i1}, U_{i2}, \ldots, U_{i\,J+1}) \qquad (6)$$

Where U_{ij} is utility function from provider *j* and *j = 1, 2, …, J+1*

The solution to (6) gives the health care alternative that is chosen. Note that provider j is chosen if and only if $U_{ij} > U_{ik}$ for all $k = 1,\ldots, J+1$, $k \neq j$. Then the conditional utility function of provider j can be computed by solving for C_j from (4) and substituting (4) and (5) in (3) as follows.

$$U_{ij} = U(H0 + Q_{ij}(X, Z), Y - [P_{ij} + wT_{ij}] + \varepsilon_{ij})\ldots \qquad (7)$$

As long as the conditional utility function, U_{ij}, in (7) is quasi-concave in H_{ij} and C_{ij} and H_{ij} and C_{ij} are greater than zero, there exists a conditional indirect utility function (with all of its property of quasi-convexity, and decreasing in prices and increasing in income) given by

$$V_{ij} = V(P_{ij}, wT_{ij}, H0, Q_{ij}(X, Z), Y, \varepsilon_{ij}) \ldots \qquad (8)$$

Equation (8) is the reduced form of the indirect utility function of alternative j and it is the bases of estimating health care demand functions in most of the literature.

Based on this fame work various attempts have made to estimate a health care demand function that is in line with utility maximisation, economic theory, and common sense and that satisfies statistical and econometric requirements. However, there are disparities in formulating a model that satisfies all of the above requirements. Consequently, basic differences can be observed in specifying the functional form of the direct and the indirect utility functions, formulating the budget constraints, deciding about the distribution of the error term, etc. In this study, we use the following flexible model of Dow (1995). Such specifications help us to see the impact of poverty (income) on the health care demand behaviour of households and to estimate different price elasticity of demand for each alternative.

An individual is expected to maximize the conditional direct utility function given by

$$U_{ij} = \alpha 1H_{ij} + \alpha 2C_{ij} {}_{*}Q_{ij} + \alpha 3C_{ij}{}^{2} \quad (9)$$

subject to the budget constraint and the health production function given as

$$Y_i = UF_{ij} + TC_{ij} + C_{ij} \quad (10)$$

$$H_{ij} = H_{i0} + Q(X_{ij}, Z_{ij}) \quad (11)$$

The result of the maximization process gives the following conditional indirect utility function.

$$V_{ij} = \alpha 1[H_{i0}+Q(X_{ij}, Z_{ij})] + \alpha 2[(Y_i - UF_{ij} - TC_{ij})(H_{i0} + Q(X_{ij}, Z_{ij}))] + \alpha 3(Y_i - UF_{ij} - TC_{ij})^2 \quad (12)$$

After some manipulations, the reduced form of equation (12) can be written as random and as a function of estimable parameters as follows.

$$V_{ij} = \varphi 0j + \varphi 1j\, X_i + \varphi 2jWT_{ij} + \varphi 3jDIS_{ij} + \varphi 4jUF_{ij} + \varphi 5jUF_{ij}{}^{*}Y_{ij} + \varphi 6jTC_{ij} + \varphi 7jTC_{ij^{*}}\, Y_{ij} + \varepsilon_{ij} \quad (13)$$

Where

X represents a vector of individual characteristics,

WT is the waiting time in health care provider j,

DIS is distance of provider j to individual i,

UF represents user fee,

UF*Y is the interaction between user fee and income,

TC is the transport cost to get treatment from provider j, and

ε represents unseen variations in tastes, errors in perception of attributes of alternatives, etc.

Note that the coefficients of the variables have j as subscript indicating that they are allowed to vary across alternatives.

As we have seen before, individual i who faces j+1 health care alternatives is assumed to choose the health care provider that gives the highest utility from consuming its service. This implies that health care provider j will be chosen if and only if $U_{ij} \geq U_{ik}$ for all k = 0,1,2…J, k ≠ j. Therefore, in a discrete chose model, the health care demand schedule of individual i can be approximated by the probability that the utility from alternative j is higher than any other alternative.

Let Yi be a random variable which can take any one of the values of 0, 1, 2, …, j alternatives. Further assume that the disturbance terms in equation (13), i.e. $(\varepsilon_{i0}, \varepsilon_{i1}, \varepsilon_{i2, \ldots,} \varepsilon_{iJ})$

have a generalized extreme value (GEV) distribution and are allowed to correlate within sub groups. This gives us a nested multinomial logit (NMNL) model. The NMNL model nests the choice of providers within the first big decision of whether to seek care or not. Based on NMNL model McFadden (1981) has shown that the probability that individual i will choose alternative j from branch l (Yi = j/l) can be expressed as

$$\pi_{ij} = \frac{\left(\sum_{k=0}^{J} e^{v_{ik}}\right)^{\sigma}}{e^{V_{i0}} + \left(\sum_{k=0}^{J} e^{V_{ik}}\right)^{\sigma}} \frac{e^{V_{ij}}}{\sum_{k=0}^{J} e^{V_{ik}}} \tag{14}$$

Where

π_{ij} = the probability of choosing health care alternative j from branch l ,

V_{i0} = the conditional indirect utility function associated with self alternative

V_{ij} = the conditional indirect utility function from the alternative chosen,

σ = the measure of similarity or substitutability within a nest

Note that the term in the bracket is known as the inclusive or dissimilarity value and its parameter (σ) is one minus the correlation between the error terms of grouped alternatives (McFadden 1981). If σ is equal to one it implies that the correlation of the disturbances within the group is zero and the NMNL model will collapse to MNL model. On the other hand, if σ is zero the correlation between the error terms of the nested groups is 1 and this implies that each alternative should be estimated independently. Therefore, the parameter of the inclusive value should lie within a unit interval to be consistent with a stable utility maximization (McFadden 1981, Maddala 1983, Greene1997). We use this parameter to test whether the groping or the nesting structure of our model is appropriate. Whenever the hypothesis that $\sigma = 1$ is rejected it implies that either the groping or the NMNL model is not appropriate.

3.2. Measurement of Variables and Descriptive Statistics

In a conditional discrete choice model, the dependent variables are measured by the types of health care providers selected for treatment. Therefore, five dependent variables, namely hospital, public clinic or health centre, private clinic, traditional, and self-care are identified. The self option captures those individuals who reported illness but did not seek any outside medical help. Table 4 presents the description of the dependent variables and the percentage of individuals in each category.

The independent variables are divided into individual, household and access variables. The first group includes characteristics of individuals that are assumed to affect the probability of getting medical help and the efficacy of medical care including age, sex, relation to the household head, and severity of illness. The household level variables are expected to capture the characteristics of the decision maker. These include sex, age, and the educational level of the household head and the income level of the household. The sample mean values of all these variables are shown in Table 4.

Table 4. Description of Variables

Variables	Description (Recall period was 12 months)	Indicators
	Dependent Variables*	%
Hospital	1 if the individual was sick and visited hospitals and 0 otherwise	9.4
Clinic	1 if the individual was sick and visited government health centres or clinics and 0 otherwise	29.5
Private clinic	1 if the individual was sick and visited private clinic, pharmacies or home of health workers and 0 otherwise	27.4
Traditional	1 if the individual was sick and visited traditional healers including Holly water and 0 otherwise	7.2
Self	1 if the individual was sick but did not seek any outside help & 0 otherwise	26.5
	Explanatory Variables	Average
Sex	1 if the individual is male and 0 otherwise	0.51
Age	Age of the individual in years	24.5
Age square	Age square of the individual in years	946.9
Relation	1 if the individual is spouse, son or daughter of the head & 0 otherwise	0.92
Sex of the head	1 if the head of the household is female and 0 otherwise	0.15
Age of the head	Age of the household head in years	46.32
Education head	1 if the head of the household the individual belongs can read and write	0.55
User fee_h	The price charged by hospitals	212
User fee_c	The price charged by health centres /clinics	40
User fee_p	The price charged by private clinics	62
User fee_t	The price charged by traditional healers	71
W time_h	Waiting time in hospital in hours	4.59
W time_h	Waiting time in health centres/clinics in hours	2.15
W time_h	Waiting time in private clinics in hours	2.04
W time_h	Waiting time in traditional healers in hours	1.68
Distance_h	Distance to the nearest hospital in walking hours	4.16
Distance_c	Distance to the nearest health centres/ clinics in walking hours	1.06
Distance_p	Distance to the nearest private clinic in walking hours	1.14
Distance_t	Distance to the nearest traditional healer in walking hours	7.22
Log income *user fee	Log of annual farm and non farm income of the household the individual belongs in Birr times user fee	513

*If more than 1 visits were made the most recent one was considered

The access variables include user fees (including consultation, laboratory, and drug costs), transport costs, distance, and waiting time costs. In discrete choice model, every individual is assumed to know the price, quality, and other features of all available providers in the area. As a result, information about each individual and provider is expected to be available irrespective of the choice made. However, it is very difficult to get information from respondents about the alternatives they did not visit. Usually different procedures are followed to overcome this problem. The first method is to combine the household level survey with health care provider surveys to fill the information gap on providers' characteristics (Akin et al 1985, McNamara 1999). The second method is to use a hedonic pricing approach (Wedig 1988, Dicowsky 1991, Gertler and Gruber 1997). The third method is to compute the village level mean or median values of the access variables for each alternative based on users' information and to use these values for each individual within the village irrespective of individual characteristics (Hallman 1999, Li 1996, Dor 1986). Some researchers have also used the combination of the three methods based on the level of the availability of data for each individual and alternative (Dor 1988). In this study, the third method is used to compute user fees, waiting time, and distance variables for each village.

3.3. Estimation

To select the best grouping structure among the different possible specification of the conditional models, the validity and significance of the coefficients of the inclusive values are examined. Table 5 shows the results from estimation of the NMNL model. The coefficient of the inclusive value (σ) should lie between 0 and 1 to be consistent with a stable utility maximization. In the first case, ill individuals are grouped into demanders (hospital, clinic, private clinic, traditional healers) and non-demanders (self option). In the case of non-demanders σ is constrained to be one since we have only one alternative in this branch. As the table shows the estimated value of σ is greater than one, which rejects the grouping of all demanders in one branch.

Table 5. Different Nesting Structures of the Conditional Demand Models and the Value and Significance of the Coefficient of the Inclusive Value

Nesting Structure	Coefficient of the Inclusive Value	Implications
Seek (hospital, clinic, private clinic, traditional) Not seek (self)	1.316* (3.411) 1.000^{+}	The coefficient of the inclusive value for the first group is greater than 1implying that the groping is not consistent with stable utility maximization.
Modern (hospital, clinic, private clinic) Traditional (traditional) Self (self)	0.582* (0.218) 1.000^{+} 1.000^{+}	The coefficient of the inclusive value for the first group is between 0 and 1 and significant implying that the grouping is consistent with stable utility maximization theory.
Modern (hospital, clinic, private clinic) Non-modern (traditional, self)	0.026 (0.175) -2.091** (0.948)	The coefficient of the inclusive value for the first grouping is not significant and for the second it is negative. Therefore, the grouping is not consistent with the theory.

+ Fixed parameter
Figures in parenthesis are standard errors.
* Significant at 1 and less than 1% confidence level
** Significant at 5 and less than 5 % confidence level
*** Significant at 10 and less than 10% confidence level

Therefore, an attempt is made to nest the traditional healer alternative from other alternatives to make it as one separate branch as shown in the second raw of Table 5. In this case, in addition to the self-care alternative the inclusive value parameter for the traditional alternative is also constrained to be one for the same reason given above. The coefficient of the inclusive value for the alternatives nested in modern branch is now 0.525 and significant at less than 1 percent significance level. This indicates the existence of correlation among the unobserved components of these alternatives and estimating a simple multinomial logit model may give biased results. It also shows higher degree of substitutions among the modern health care options than other alternatives. Other nesting structures have been also tried but none of them was consistent with stable utility maximization. Therefore, though the difference in the results is minor, the nesting structure that categorizes individuals into three (modern health care, traditional and self) is selected for further analysis.

3.4. Effects of Poverty on the Probabilities of Choice

Table 6 provides the probability weighted average marginal effects of different covariates on the probability of seeking medical care and provider choice[7]. As it can be seen form the table, the impact of a change in any one of the covariates can be decomposed into two: the effect on the probability of choosing a certain branch and the effect on the probability of choosing a specific alternative within that branch. For instance, a one Birr increase around the mean hospital user fees value is likely to reduce the probability of individuals to choose modern health care providers by 0.024 percent and the probability of choosing hospital alternative within modern providers by 0.234 percent. This implies that a one Birr increase in the user fees of hospitals reduces the likelihood that the hospital alternative will be chosen by a total of quarter of a percentage.

Table 6. Marginal Effects of Different Covariates on Probabilities of Health Care Provider Choice of Rural Households*

Choices	Probability of Choice	Direct derivative effects+ of					
		User fee	Distance	User fee * income	Relation	Education	Severity
Hospital	Modern branch	-0.024	-0.336	0.002	1.567	1.031	1.609
	Hospital	-0.234	-3.340	0.017	15.570	10.239	15.981
	Total	-0.258	-3.676	0.019	17.137	11.270	17.590
Clinic	Modern branch	-0.200	-	0.013	4.339	4.876	2.422
	Clinic	-0.751	-	0.048	16.305	18.323	9.103
	Total	-0.951	-	0.061	20.644	23.199	11.525
Private Clinic	Modern branch	-0.050	-	0.012	5.799	3.169	3.163
	Private clinic	-0.236	-	0.058	27.164	14.845	14.817
	Total	-0.287	-	0.070	32.962	18.014	17.980
Traditional	Traditional branch	-0.171	-	0.042	19.684	10.757	10.737
	Traditional choice	0.000	-	0.000	0.000	0.000	0.000
	Total	-0.171	-	0.042	19.684	10.757	10.737

* Marginal effects are computed only for significant variables

+ Derivatives are multiplied by hundred

The impact of relation to the head on health care demand and on the choice of providers is impressive. Ceteris paribus, being an immediate family member of the head increases the

[7] Marginal effects are computed only for significant variables since we are interested to know their magnitude of influence.

predicted probability of seeking out side medical care by 90.43, modern providers by 70.74 and private providers (within modern providers) by 46.59 percent. This implies that the probability of other family members to seek outside care in the case of illness/injury is less than 10 percent and if they have any chance to get out side help, it is less likely to be in private and government clinics compared to traditional healers and hospitals. This may indicate that the health problem of non-immediate family members is perceived by decision maker(s) of the household only when it becomes serious usually beyond the capacity of both private and government clinics. As expected, severity of illness increases the predicted probability of seeking outside medical help particularly from hospitals, private clinics, and traditional healers respectively.

Our main interest, however, lies on investigating the impact of poverty on probabilities of health care provider choice. As the table clearly shows, user fees, especially that of public clinics, have negative and significant impacts on the demand for medical care compared to all other access variables. Specifically, the results show that a one Birr increase in the user fees of public clinics has eight times more negative impact than hospitals and four times than private clinics in shifting individuals out of modern health care alternatives to traditional and self care options. However, as can be seen from the positive sign of the income user fee interaction variable, income plays a significant role in neutralizing the negative impact of user fees on the choice of providers. This is specifically important in the case of private and public clinics. This implies that poverty affects negatively the probability of the poor to choose modern health care providers such as private and public clinics. Distance appears to have a negative and significant impact on the hospital alternatives to be chosen but to have no significant impact on other choices. Probably this can be due to the absence of big variation in distance between private and government clinics. Compared to the highly significant coefficient of user fee and user fee income interaction variables this result may indicate that demand side problems are more important than supply side problems.

3.5. Impacts of user fees on the poorest of the poor

Increasing user fees is one of the options of generating additional resources for the health sector. However, the impact of raising user fees on the utilization of health care services should be thoroughly investigated before this way of generating income is suggested for policy makers. The impact of user fees on the demand for medical care and on provider choice can better be analysed via price elasticities of demand. Price elasticities of demand provide accurate pictures to examine the possible negative impacts of user fees on health care utilization of households.

In the case of NMNL model, the price elasticity of demand is defined as the percentage change in the predicted probability of demanding medical care from health care provider j of branch l as a result of one percentage increase in the user fess of the same provider j. The cross price elasticity of demand is also defined in the same fashion. Both the own and the cross price elasticities of demand are computed based on the marginal coefficients presented above.[8]

Economic theory suggests that the price elasticity of demand may not be the same for different income groups. Therefore, we have tried to see the responsiveness of demand for changes in user fees of different providers between the poorest (the lowest income quartile) and the relatively non-poor (the remaining quartiles) households. Table 7 presents the results.

As the table clearly shows, the poorest segment of the population is extremely sensitive for price changes of almost all providers. If we concentrate on modern health care providers, the table depicts that a 1 percent increase in the user fees of hospitals is likely to reduce the probability of individuals from the poorest families to seek hospital care by 9.18 percent compared to only by 2.42 percent in the non-poorest families. The own price elasticity difference is much higher in the case of private clinics. However, if we see the cross effects of user fees on deciding to join the health care market, poor people are more sensitive to the price of government clinics than other alternatives. This can be clearly seen by investigating the shift in demand within different alternatives as a result of a price rice in each alternative.

Table 5.9. Direct and Cross Price Elasticity of Demand by Income Group

Provider		Hospital	Clinic	Private clinic	Traditional	Self (No care)
Hospital	Poorest	-9.181	1.875	1.405	0.172	0.098
	Non poor	-2.419	0.282	0.333	0.174	0.122
	The whole sample	-2.572	0.318	0.353	0.201	0.140
Clinic	Poorest	10.564	-6.787	6.081	0.723	0.669
	Non poor	0.082	0.180[9]	0.101	.039	0.043
	The whole sample	0.412	-0.822	0.489	0.187	0.222
Private clinic	Poorest	6.274	4.065	-14.473	0.776	0.494
	Non poor	0.501	0.314	-0.61	0.198	0.163
	The whole sample	0.463	0.299	-0.701	0.199	0.163
Traditional	Poorest	0.172	0.723	0.776	-27.762	1.724
	Non poor	0.174	-0.039	0.198	-1.022	0.067
	The whole sample	0.126	0.058	0.101	-0.103	0.069

For the whole sample a 10 percent increase in clinic user fees, ceteris paribus, increases the probability of a person not to seek any outside care by 2.2 percent. The corresponding figure for the chronically poor, however, is 6.69 percent, which is three times higher than the average figure. If the user fees in all alternatives are increased simultaneously by ten

[8] See Greene 1997, 1998, Long 1997, and Bitran 1994 how elasticities can be computed in the case of NMNL models.

[9] This is not a normal sign for prices elasticity. However, it may indicate that a price rise at government clinics may not be a barrier for the non-poorest part of the sampled households. Some positive price elasticities are also reported by Escobar (1990) and Mortimer (1997).

percent, all other things remaining constant, nearly 30 percent (0.98 +6.69+ 4.94 +17.24) of the poorest of the poor will be driven out of the health care market compared to 6 percent for the whole sample. These clearly demonstrate that increasing user fees in any of the alternatives especially in traditional healers and government health centres and clinics is likely to drive out a significant portion of the poorest households and the most venerable individuals within households from the health care market.

This has far reaching policy implications especially in the area of cost recovery and in improving the health status of the poor and reaching the chronically poor. Though user fees are not new for most of rural Ethiopians and are a good source of revenue for the health sector, increasing them beyond their current level may not only discourage people from demanding outside medical care but may also be highly regressive. A substantially high segment of the poor will be driven out of the health care market, which will aggravate the current inequality in access for basic health care services in the country. However, one has to take these results in caution since the analysis does not take into account the issues of improvements in quality and access. Probably the negative impact of a rise in user fees in discouraging people from demanding health care may not be as strong as reported above if the price increases are accompanied by quality and access improvements. Further detail research needs to be done in this respect.

4. CONCLUSION

Health care demand analysis has paramount importance in analysing the impact of poverty on the health care demand behaviour of households. It also helps to investigate the impact of various health related policy measures such as cost recovery on the poor and on the deprived and socially excluded individuals within households. Using a discrete choice model (developed based on the micro-economic theory of random utility maximization), this study investigates the impact of poverty on health status, decision to seek medical care and health care provider choice of rural households in Ethiopia. It also examines the impact of increasing user fees on the health care demand behaviour of the poorest segment of the population.

The results of the study show that instead of gender and age, relation to the head of the household is an important factor that affects the health status, demand for medical care, and provider choice of households. Immediate family members are more likely to report illness, to get treatment, and more likely to visit modern health care providers especially private clinics than other family members.

The results also demonstrate that poverty has an inauspicious impact on the health status and health care demand behaviour of households. The poor are more likely to fall ill but less likely to get out side medical help compared to their rich counterparts. This implies that the rich have disproportionately benefited from the existing subsidies of the government to public health care providers. Poverty not only directly affects the health status of individuals but also increases the duration of illness and hampers the cross effect of other variables such as education on reducing the incidence of illness, seeking outside medical care, and choosing modern providers. For instance, the cross effect of mothers' education in the decision to seek outside medical help (given illness) is 10 times less for the poorest of the poor compared to other income groups.

User fees have a very strong negative impact on utilization of medical care compared to all other access variables such as distance and waiting time especially on the chronically poor households. The nested multinomial logit results reveal that the demand reduction effect of user fees on the poorest segment of the population is substantially higher than the relatively non-poor. If the user fees at all providers increase simultaneously by ten percent, the probability of seeking outside medical care declines by 6 percent for all individuals but by 30 percent for the chronically poor individuals. These results indicate that policies designed to generate additional financial resources by increasing user fees may not be achieved without significantly crowding out the socially disadvantaged and the poorest segment of the population from the health care market. This may in turn push the poor to the vicious circle of poor health - poverty. On the other hand, preventive measures such as vaccination (especially for kids) and having latrine and separate room for animals can reduce the incidence of illness by one third. This is an interesting result since most preventive measures can be done by the community themselves without putting additional financial burden on poor households and the government.

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Appendix1. Binomial Probit Model: Determinants of Incidence of Illness considering Income as Exogenous Variable

Variables	OLS results	Maximum likelihood results	
	Coefficients	Coefficients	Marginal Effects
Sex	0.0026	-0.0075	
	(0.0279)	(0.0849)	
Age	0.0015	0.0037	
	(0.0020)	(0.0059)	
Age square	-0.0000	-0.0000	
	(0.0000)	(0.0000)	
Sex * Age	0.0004	0.0017	
	(0.0010)	(0.0030)	
Vaccination	-0.1225*	-0.4027*	-0.1399*
	(0.0339)	(0.1071)	(0.3718)
Vaccination * Age	0.0029*	0.0093*	0.0032*
	(0.0011)	(0.0033)	(0.0011)
Literacy of the head	0.6048*	0.1802*	0.0626*
	(0.0205)	(0.0611)	(0.0212)
Literacy of mother	-0.0056	-0.0313	
	(0.0228)	(0.0687)	
Family Size	0.0065***	0.0191***	0.0066***
	(0.0037)	(0.0111)	(0.0039)
Log income	-0.0518*	-0.1486*	-0.0516*
	(0.0073)	(0.0216)	(0.0075)
Relation to the head	0.0779*	0.2879*	0.1001*
	(0.0281)	(0.0921)	(0.0319)
Latrine	-0.1161*	-0.3864*	-0.1343*
	(0.0223)	(0.0709)	(0.0246)
Share room with animal	0.0223 (0.0196)	0.0587 (0.0589)	
Constant	0.5804*	0.2583	
	(0.0769)	(0.2336)	
No of observations	2690	2690	
Log likelihood function		-1565.794	
Restricted log likelihood		-1670.229	
Chi – squared (Significance level)		208.86 (0.0000)	

Figures in parenthesis are standard errors
* Significant at 1 and less than 1% confidence level
** Significant at 5 and less than 5 % confidence level
*** Significant at 10 and less than 10% confidence level