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Demand for Health Care in Kenya: The Effect of Health Insurance

Josephine Gakii

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Social Sector Division
Kenya Institute for Public Policy
Research and Analysis

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Abstract

The health of the general population has been a major concern of the Government of Kenya since independence. There is evidence suggesting that positive health outcomes can be achieved if health care is made broadly available to the population during illness episodes. Moreover, it is widely believed that access to health insurance is one crucial mechanism for enabling all social groups to obtain care in the event of sickness. However, little evidence exists in Kenya on effects of health insurance on health status or on demand for health care. Indeed, substantial uncertainty exists in the literature regarding effects of health insurance on health and on health care provider choice decisions.

This paper is an attempt to shed light on these issues. It investigates the role of health insurance on health status, health care utilization, and health care provider choice, controlling for individual, household, and community characteristics. Using data from the 2007 Kenya Household Health Expenditure and Utilization Survey (KHHEUS), the paper estimates probit models of health production and health care decisions conditional on illness. Further, a multinomial probit model is used to study the effect of health insurance on health care provider choice.

The empirical results suggest that health insurance is positively associated with health status of the population. Furthermore, the probability of seeking treatment during an illness episode is increased by health insurance. Moreover, health insurance is shown to divert demand from public to private care providers, although government health facilities still remain the single largest health care sources for the population, even in the simulated event of universal health insurance coverage. The simulation results suggest that health service utilization would still remain low under universal health insurance coverage because non-insurance factors importantly affect health service usage. The policy implications of these findings and some recommendations are discussed in the concluding section of the paper.

Abbreviations and Acronyms

IFC	International Finance Corporation
KDHS	Kenya Demographic Health Survey
KHF	Kenya Healthcare Federation
KHHEUS	Kenya Household Health Expenditure and Utilization Survey
KIHBS	Kenya Integrated Household and Budget Survey
KNBS	Kenya National Bureau of Statistics
KNH	Kenyatta National Hospital
KSH	Kenya Shillings
NHIF	National Health Insurance Fund
NGO	Non Governmental Organization
SAH	Self Assessed Health Status
WHO	World Health Organization

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1.   Introduction

1.1   Background

Good health is globally recognized as a fundamental human right for all (World Health Organization-WHO, 2007). As the population strives to acquire good health, demand for health care increases. The increase in demand for health inputs has prompted greater investments in health care programmes, both in public and private sectors. An increase in the range of health services available enables patients to access different health care providers in accordance with their preferences. However, since the public-private mix of health providers differs from country to country, the pattern of health services utilization by patients across health system sub-sectors differs from country to country, due to differences in disease burdens in the population and medical care specialization of providers. For example, in Singapore, outpatients enjoy freedom of choice between the equally easily accessible private (80%) and public (20%) clinics (Meng-Kin, 2004). Even in the context of a good mix of public-private health care provision, governments must remain as the guardians of public health. This is because the health of an individual is characterized by social positive externalities. For example, when an individual is cured of an infectious disease, other members of the society are protected from the disease. Moreover, the innovativeness and productivity of a healthy individual can yield benefits not only to that individual, but also to his/her family and the wider community.

In sub-Saharan Africa, the shares of health care industry held by both public and private sectors vary widely across countries and regions based on a variety of political, historical, and economic factors. In some countries, the private sector is considerably large, and constitutes an important and diverse source of the region's health care. In countries like Uganda and Ghana, usage of private sector services comprises over 60 per cent of the total visits to all providers, while in others such as Namibia, it is less than 10 per cent. The private sector cares for people from a wide distribution of incomes, including the poor, the urban and rural residents. For example, in Ethiopia, Kenya, Nigeria, and Uganda, more than 40 per cent of people in the lowest income quintile receive health care from private-for-profit providers (International Finance Corporation-IFC, 2006). When the services of faith-based organizations and other non-profit entities are included, the coverage of poor and rural populations by the private sector increases considerably. Surprisingly, in many sub-Saharan African countries, it is the wealthy and not the poor who disproportionately benefit from public health spending. For example, in Mauritania, 72 per cent of hospital subsidies benefit the richest 40 per cent of the population (IFC, 2006).

In Africa, as in other world regions, health care services are financed broadly through public and private expenditure, as well as external aid. The public expenditure comprises general government revenues, and the government sponsored self insurance schemes such as the national hospital insurance fund, while the private health costs are financed by the fees paid by individuals to providers at the point of service use. The user fees typically finances medical treatments at private health facilities, complemented by insurance premiums and other forms of prepayments that can also be used to access care in the public health system.

1.2   Overview of the Kenyan Health Sector

In Kenya, health care provision is through a network of diverse providers. They comprise government, private-for-profit, and voluntary agencies (faith based organizations, missions, and non governmental organizations). However, the type of health services offered differs across these health care sub-systems. For example, public care encompasses preventive, promotive, curative and rehabilitative services, while NGOs and the private providers concentrate on curative services with limited provision of preventive services (Kenya Healthcare Federation-KHF, 2009). The health sector obtains varying levels of funding from traditional sources: public (government), private firms, household and donors.

Public health services are provided through a network of provincial, district and sub-district hospitals, health centres, sub-centres, and dispensaries. In the rural areas, health services are mainly provided through the health centres and dispensaries. Kenyatta National Hospital (KNH) is at the apex of the health system and is operating as the central referral and teaching facility.

With Kenya being predominantly a free market economy, the price of health care in the private health sector is largely determined by the forces of demand and supply. This means that some people, especially the poor, can easily be locked out by the market system, and thus from accessing and utilizing essential health care services. However, since health care is a merit good, and the government is the largest provider and financier of health care, this good is heavily subsidized in public clinics and is generally accessible by the poor. However, this may not be sustainable as the government's fiscal resources are overstretched. Therefore, as part of the structural reform under the Structural Adjustment Programmes (SAPs), cost sharing was introduced in the health sector (Ngugi, 1999). Under the arrangement, consultation fees was introduced and were later converted to treatment fees in 1992. The fee aimed at enhancing the financial capacity of the government and improving the quality of health care. Expectation was that there

will be increased access to health care for all. However, evidence shows that in 2006, 30 per cent of individuals who reported being ill (four weeks prior to the survey) did not visit any health care provider, while 52.2 per cent and 48 per cent of the remainder visited public and private providers, respectively (Kenya National Bureau of Statistics, 2005/2006).

However, a study by Ellis (1987) on health care in Kenya conducted before the introduction of user fees postulated that even small increases in user fees can potentially raise revenue but would exclude a large proportion of the population from accessing health care. Likewise, after the introduction of user fees, Mwabu and Wang'ombe (1997) showed that an increase in user fees (however modest) can lead to substantial reduction in demand for health care even when demand is price inelastic. Further, Bedi *et al.* (2004) found that an increase in price of health services diverts demand from public to private facilities.

The introduction of user fees in the 1990s did not satisfactorily meet the expectation of increased demand and utilization in Kenya, prompting the quest for an alternative health financing strategy that will ensure access to health care and equity in provision of health care services to all. Health insurance is deemed as one such avenue. However, inequities are also very apparent in accessing health care in Kenya, even among persons covered by medical insurance schemes. In relation to accessing medical insurance, middle and high income earners are able to pay for private insurance relative to the poor. In addition, the population covered by private health insurance schemes remains very small. Public health insurance via the National Health Insurance Fund (NHIF), though compulsory, caters mainly for the formally employed, with only a small proportion of the informal sector workers benefiting from the fund.

The government envisions introducing a national social health insurance that will provide health care insurance for the entire population. This is aimed at increasing access to health care and utilization as well as improving health outcomes. However, the prospect for a national social health insurance scheme raises several questions: What would be the demand for health care pattern that would result from a system of insurance for health care services? In addition, how does the medical insurance help in improving health outcomes of the population? This is the focus of this study as it seeks to establish the role of insurance in the demand for health care and in reducing disparities in health outcomes in the population.

1.3   Problem Statement

In Kenya, more than two-thirds of the burden of disease is due to communicable diseases (71%), non-communicable diseases (22%), and the rest (7%) due to injuries (WHO, 2008). However, the country faces an increasing health burden from injuries and non-communicable diseases. Projections show that deaths due to communicable diseases in Kenya are expected to decrease over the years (by around 13% in 2030), while those from non-communicable diseases are expected to rise over the years (Mathers *et al.*, 2006).

A high burden of disease affects the productivity of an individual and the state of being ill is undesirable. Positive health outcomes are therefore associated with access and utilization of health care. If people are not utilizing medical services, then poor health can persist. Existence of disparities in levels of access and service utilization leads to inequalities in health outcomes. One of the major determinants of the utilization of health care services is the cost of care. An important mechanism through which health disparities in the population can be reduced is to cut the cost of care at the point of utilization through, for example, the use of health insurance rather than subsidies or free provision of health services.

An attempt to explain the link between health insurance, health status and choice of health care provider has been made on the rural population in Kenya, but not the entire population. However, exploration of effects of interactions between health insurance and socio-economic variables on health status, health service utilization or on choice of health care provider is missing in literature. This study fills this gap by computing the full effect of health insurance interacted with socio-economic variables on health outcomes of males and females for the entire population.

1.4   Research Questions

This study is guided by the following research questions:

(i)   Why are there inequalities in health outcomes in the population?

(ii)   What determines the decision to utilize health care?

(iii)   What determines choice of treatment at a particular health care provider?

(iv)   What is the role of health insurance in determining health status and overall health care demand?

1.5   Study Objectives

The overarching objective of the study is to examine the demand for health care in Kenya, with specific emphasis on the role health insurance plays in the production of health and in influencing demand for health care.

The specific research objectives are to:

(i)   Determine what distinguishes people who report being ill from individuals who do not report illness.

(ii)   Determine factors that influence the demand for health care from specific providers.

(iii)   Establish the effect of insurance on health status, controlling for effects of other covariates using a health production function.

(iv)   Establish the effect of insurance on choice of providers, controlling for effects of other covariates using a provider choice model.

(v)   Determine the factors that influence the decision to seek care conditional on reporting illness.

(vi)   Suggest recommendations that can be used to increase health service demand in Kenya in a way that would reduce health disparities in the population.

1.6   Justification

The Government's vision for the health of its citizens in its economic blueprint Vision 2030 is to provide equitable and affordable health care at the highest affordable standard. In order to achieve this, the Vision recognizes that a functional health system has to be put in place. Such a system should increase access to health facilities and essential medicines, in order to improve health outcomes.

An important feature of a viable health system is a financing system which guarantees access to quality health care for all Kenyans, especially the poor. One financing alternative is the NHIF, which reduces the cost of care at the point of utilization. It is hoped that the provision of health insurance will guarantee universal availability, accessibility and affordability of essential health services. Understanding the effect of health insurance on health status as well as on the utilization of health services, will contribute to generating more knowledge in this area as the Government strives to have an optimal financing mix.

This study also extends the existing literature on choice of alternative health care providers by examining in detail the effect of medical insurance on choice of

specific health care providers. The study generates information that policy makers can use to design and implement health care financing strategies that promote equitable health outcomes in the population.

2.   Literature Review

2.1   Theoretical Literature

According to Grossman (1972a), good health can be viewed as a commodity which is produced by individuals and households. In essence, people are viewed as producers of health based on the choices they make about their behaviour and medical use. With the basic economic principle that people respond to incentives (Mankiw, 1998), then the choices they make may promote or destroy their health. These choices are however constrained by finance, time, initial health endowment, social and natural environments (Mullahy, 2010).

Health can therefore be demanded as a consumption commodity as well as an investment commodity. As a consumption commodity, health directly enters individuals' preference functions; while as an investment commodity, it determines the total amount of time that an individual can devote to market and non market activities (Grossman, 1972a).

With the assumption that individuals inherit an initial stock of health that depreciates over time and that these stocks can be increased by investment, then inputs are needed to produce health. One of the many inputs that people may invest in is medical care, which is seen as increasing the stock of health in addition to increasing market and non market productivity through better health. Under certain circumstances, households can be assumed to invest in health production until the marginal cost of health production equals the marginal benefits of improved health status (Grossman, 1972b). In this framework, differences in efficiency of production of health cause inequalities in health outcomes.

Drawing on the theory of human capital by Becker (1965) in the economics of household production, Grossman (1972b) constructs a model where households combine purchased goods and services and their own time to produce health. It is assumed that given the amount of medical services that a group of individuals consumes and some socio-economic variables (which are referred to as environmental variables), it should be possible to predict what the health of the group will be.

The individuals demand for medical care is however irregular and unpredictable (Arrow, 1963). This means that if an individual is ill, the preferable option is to seek medical care so as to improve his or her health. In these types of models, medical care is a commodity over which individuals have preferences (Phelps, 1992). The expected utility individuals derive from each medical care source guides the choice of care. The choice of care is valued up to the point it is seen

to improve the health of an individual. In addition, the utility of the preferred provider has to be greater than that of the other providers. However, if individuals are risk averse, they would prefer to have health insurance to protect them from out of pocket payment.

Arrow (1963) postulates each individual as acting so as to maximize the expected value of a utility function. Here utility is hinged on income such that individuals experience diminishing marginal utility of income. Since these particular individuals are risk averse, they would prefer to be insured rather than face the random costs of health care.

2.2   Empirical Literature

Studies on the relationship between medical insurance and health status using mortality as a measure of health status suggest that health insurance could reduce the mortality rate of those who were previously uninsured (Hadley, 2003; McWilliams *et al.*, 2004; Hadley and Waidmann, 2006). Existing literature has also suggested that there are significant positive effects of health insurance on self-reported health status (Franks *et al.*, 1993; Card, Dobkin and Mastas, 2008; McWilliams *et al.*, 2004; Hadley and Waidmann, 2006; Hong *et al.*, 2009). Although much of the existing literature demonstrates the positive relationship between being covered by health insurance and health status, several studies have found that health insurance coverage is not associated with better health (Ellis and Mwabu, 2004) and some studies have even found insurance to be associated with worse health status (Hadley, 2003). As a result, very few studies have been able to draw firm conclusions about the causal relationship between health insurance and health status (Levy and Meltzer, 2001; Hadley, 2003; Chen *et al.*, 2007). A RAND experimental study demonstrated that health insurance is only useful to those who were chronically ill (Manning *et al.*, 1987), a view also supported by Cameron *et al.* (1987). The literature is inconclusive in this area.

Grossman (1972b) argues that higher incomes do not necessarily lead to higher levels of health, even on an average. He has shown this theoretically and empirically and explains that higher incomes may also induce higher levels of consumption of other goods and services that have negative effects on health. To corroborate this finding, Kaplan *et al.* (1996) using mortality as the health indicator, finds that high incomes are associated with higher mortality when education and medical care are controlled for. However, in some instances, lower incomes lead to worsening in health status (Desai, 1987).

Increased education levels are argued to be negatively correlated with ill health. Richard *et al.* (1969) using two stage least squares and ordinary least squares find

that high education results in low death rates. Likewise, Subramanian, Tim and Mauricio (2010) using a 5-point Likert scale of self-assessed health (SAH) shows that an increase in years of schooling reduces the probability of reporting poor health. Further, Bichaka and Paulos (2008) in a study on the health production function for sub-Saharan Africa using a one way panel data analysis use life expectancy and mortality (infants and children) as their health indicator and find that a decrease in illiteracy rate improves life expectancy and lowers mortality. Positive effects of education on the production of health have also been established (Grossman, 1972b; Desai, 1987). The level of education of the producer alters the efficiency of the production function (Grossman, 1972b). However, the stock of health capital possessed by a person who has completed his formal education tends to increase at first due to on job training and then decrease due to depreciation. Even if education is positively related with good health, the mechanisms through which education affects health are not well understood. With some positing that it is education that causes good health, others posit good health allows for better schooling.

An important strand of the literature has used data on SAH to study the socio-economic covariates of health status. Respondents assess their overall health using various ways such as a five-point scale from 'very good' to 'very bad', height or weight measures, life expectancy, and illness reporting. Idler and Benyamini (1997) review evidence on SAH assessments help predict subsequent mortality. On the basis of such evidence, Franzini *et al.* (2005) claim, 'Twenty years of empirical evidence indicates that SAH is a powerful and reliable predictor of clinical outcomes and mortality.'

Others have taken a more critical view of SAH data, arguing that responses on SAH are influenced by various emotional, psychological and knowledge-dependent factors. For example, Sen (1998) critiques self reported morbidity data by arguing that people will tend to adapt to situations and the environment they are in and be biased in stating their true health status. This implies that SAH may potentially exhibit reporting errors. However, recognizing the potential for reporting biases, Thomas and Frankenberg (2000) recommend that surveys combine questions on SAH with more objective indicators of health status. For example, Lindeboom and van Doorslaer (2004) use objective health data and find evidence of age and sex related reporting bias in SAH, but find no evidence of income-related reporting bias.

This study adopts the use of SAH since it has been widely used in literature. In addition, when people decide to visit a health provider, it is the SAH that the provider uses to diagnose the problem the patient has. From literature, it can be seen that the results from various data may not be applied across other countries.

This is because the disease profile, environmental and socio-economic conditions are different for different countries, and the SAH as an indicator may yield completely different results.

Health care demand studies are usually conditioned on illness. This implies that the healthy people in the population are ignored. The conditional estimates obtained may be biased from self selection. However, Dow (1995) in a study on unconditional demand for health care finds that short run demand estimates do not suffer from selectivity bias. A similar finding has been found in Mozambique by Lindelow (2005). However, these unconditional estimates differ from the long-run unconditional effects.

In the 1960s, demand for health care was hypothesized to depend on the price of that service, prices of alternative services, household income and tastes. In later years, Grossman (1972) included age, education and time costs in the demand equations and established them to be important determinants of health care utilization. This paved way for more research on health care demand, which saw additional variables of interest being specified in the models. The results vary from study to study and may be attributed to the specification of the models and type of data used.

People may be ill and are not willing to consume health care if there is payment or other charges attached (Mwabu, Ainsworth ad Nyamate, 1993). Such a scenario may arise due to the constraints that face a household and health care is relegated as a want and not a need. This may be observed in low income groups which are deemed more price sensitive than higher income ones (Ntembe, 2009). This means that, other factors being equal, the satisfaction one derives from consuming health care is higher when health care is free than when payment has to be done. However, at times, people tend to be insensitive to the price of health care (Akin *et al.*, 1986). Such indifference in consumers' consumption may be observed if the opportunity cost of ill health is very high.

Lindelow (2005) shows that income does not determine the choice of health care provider in Mozambique. On the other hand, Cameron *et al.* (1988) report that income is important in determining the health insurance choice in Australia but not in the choice of health care provider. An individual may belief that his or her level of health is determined by some uncertainty and act accordingly, for example by purchasing a health insurance, a situation associated with a number of health care issues. Becker *et al.* (1972) and Leibowitz (2004) find that health insurance induces 'moral hazard' and leads an individual to consume more health care that the patient values less than the cost of producing it. Taking the argument further, Cameron *et al.* (1988) argue that the distortion of the effective price of health care to the insured users is what may trigger the over use of the service. He then

argues that health status appears to be more important in determining the choice of provider than health insurance choice. Missing from the literature in Kenya, is the link between medical insurance, health status, production of health, demand for health care, and choice of health care providers. Ellis and Mwabu (2004) made an attempt to fill this gap using data from the rural population, but no work has been done on the topic in recent years. Moreover, Ellis and Mwabu (2004) did not explore effects of interactions between insurance and socio-economic variables on health status, health service utilization or on choice of health care providers. In modeling health production and health care demand, some variables that affect health and health care demand are assumed to depend on the level of other variables that are thought to affect production of health and demand for health care. This situation necessitates the use of interaction terms between the variable of interest such as health insurance and the conditioning variables which include income, gender or age.

Previous empirical studies on health care demand (see, for example, Ellis *et al.*, 1993; Dow, 1995; Glick, Jean and Iarivony, 2000; Lindelow, 2003) have used interaction terms in an attempt to explain the demand for health care in different countries. In presenting their results, they have evaluated the coefficient of the interaction term by simply looking at its sign, size and statistical significance. The focus on the estimated coefficient of the interaction term can be misleading because the coefficient may be biased and inconsistent and may not provide any meaningful insights. The coefficients on the interaction term may not provide the full effects of the interacted variables on health care or health outcomes. The full effects of the interacted variables can be obtained by computing direct and cross effects of the interaction term and the direct effects of the interacted variables (see Friedrich, 1982; Nagler, 1991; Ai and Norton, 2003; Norton, 2004; Brambor, Clark and Golder, 2005; Green, 2010; Berry, DeMerrit and Esarey, 2010). No study has examined effects of interaction terms in a health production function using Kenyan data. In addition, it computes the full effects of the interaction terms and interprets them. This study fills this gap by estimating the effect of insurance interacted with socio-economic variables on health outcomes of males and females.

3.   Methodology

3.1   A Theoretical Model of Production of Health

Based on Grossman (1972a), health can be thought of as a stock of human capital. At a point in time, an individual's health stock depends on the behavioural decisions concerning health. The change in the health status of a person, over time, is determined through a health production function of the form:

$$H_t = H(H_{t-1}, X_t, M_t, E_t, \varepsilon_t)..(1)$$

where H_t is the health status at time t, H_{t-1} is the previous health status, X_t is a vector of health-related inputs such as nutrition diet, exercise, and preventive care, which can be proxied by income, M_t is curative care proxied by medical insurance, E_t is a vector of individual, family and community characteristics, and ε_t is the unobserved initial endowments. The assumption here is that the use of health inputs is accompanied by health improvement.

In linear form, a health production function can be specified as:

$$H_i^* = \alpha_1 + \alpha_2 H_{t-1} + \alpha_3 X_t + \alpha_4 M_t + \alpha_5 E_i + \varepsilon_i..(2)$$

i = 1, 2... N individuals

where H^* is the observed or reported health status of an individual; and ε_t is the unobservable component. If the health of the individual falls below a certain threshold level (Z), the person reports being ill. What we then observe is a health status indicator (H^*), which takes the value of 1 if the person reports being ill during a reference period (say 30 days), and 0 otherwise; that is,

H^*=1 if $H \leq Z$, where Z is some threshold level of health status, and

$$H^* = 0, Otherwise..(3)$$

The assumption made on the unobservable component of the model (equation 2) determines the estimation method.

3.2   A Theoretical Model of Health Care Provider Choice

The model is based on a maximization random utility obtainable from seeking health care from different providers. An individual i, is faced with a set of provider alternatives j; observed characteristics of alternative j, and own attributes (X_{ij}) and those of the household to which he/she belongs. The individual is assumed to derive utility from each option j. In addition, the individual consumes both health and non-health goods. Conditional on seeking treatment, the direct utility derived

by individual *i* from provider alternative *j* can be expressed as:

$$U_{ij} = U(h_{ij}, C_{ij}) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(4)$$

where U_{ij} is the direct conditional utility that individual *i* expects from health care provider *j*; h_{ij} is the expected improvement in health status of person *i* after receiving treatment from provider *j* (this is because health status is directly related to the health care consumption through the production function); C_{ij} is the consumption of non-health care goods, the amount of which depends on choice *j* because of the costs incurred when provider *j* is chosen.

Since the expected improvement in health status (h_{ij}) is unobservable, what we observe are the socio-economic and demographic attributes of individual *i* as well as the provider specific attributes faced by individual *i* in facility *j*. Similarly, the monetary value of consumption of non-health care goods (c_{ij}) is also unobservable. The individual achieves this level of consumption, only after paying for medical care at provider *j*.

However, the decision on consumption of both the health and the non-health goods is guided by the budget constraint that faces the individual, which is expressed as:

$$Y_i = P_i C_{ij} + HP_{ij} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(5)$$

where Y_i is the annual income, HP_{ij} is the total price paid to provider *j* for health care (this is determined by both monetary and non monetary factors), and PC_{ij} is the cost of non health goods.

Equations (4) and (5) determine the general specification of a behavioural model of health care demand. In order to implement the model, we choose a functional form for the utility function in equation (4). The functional form for the utility function that is chosen should obey the axioms of preferences in consumer choice theory as shown by Gertler and Van der Gaag (1990). If, for example, a utility function is linear in health status and quadratic in consumption, it is consistent with well ordered preferences.

Identification of the behavioural parameters is ensured by the variations in monetary prices across health care providers. In addition, it is necessary to allow for non constant marginal rate of substitution of commodities in consumption. With this, empirical health care demand can be shown as consistent with the assumption that ill individuals maximize an indirect conditional utility function, v_{ij}, as shown in equation (6).

$$V_{ij} = v_{ij}(X_i, Z_i, Y_i, P_{ij}, P_{in}) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(6)$$

where X_i are the observable socio-economic and demographic characteristics of individual i; Z_j are the observable provider specific attributes faced by individual i in facility j; Y_i is the annual household income; P_{ij} is the price of health care received by individual i from provider j; and P_{in} is the price of non-health goods consumed by individual i. Equation (6) therefore shows the maximum utility that individual i can achieve, conditional on seeking treatment, controlling for X_i, Z_j, Y_i, P_{ij} and P_{in} which are all observable. In most cases, P_{in} is normalized to unity for ease of econometric calculations.

The complexity of human behaviour suggests that a choice model should explicitly capture some level of uncertainty. With the assumption that the individual has perfect discriminatory capability in his demand for health care, there exists incomplete unobservable information that creates uncertainty and therefore, this uncertainty must be captured. Therefore, the utility function in equation (6) is modeled as a random variable in order to reflect this uncertainty. This can be expressed as:

$$v_{ij} = v_{ij}^* + \varepsilon_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(7)$$

where V_{ij}^* is the deterministic part of the utility, and ε_i is the stochastic part, capturing the uncertainty.

With the assumption of the deterministic part that the utility of each alternative must be a function of the attributes of the alternative itself and of the individual; then the deterministic part of the utility that individual i is associating with alternative j is expressed as:

$$v_{ij}^* = v_{ij}^*(\beta x_i) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(8)$$

where V_{ij}^* is a vector containing all attributes, both of individual i and alternative j, and ε is a vector of parameters to be estimated. This function is generally assumed to be linear in parameters if n attributes are considered.

3.3   An Empirical Model of Health and Health Provider Choice

This study follows Ellis and Mwabu's (2004) multistage decision making process in the choice of a health care provider. In this model, the first decision is on whether or not an individual decides to report illness or injury. Second, conditional on reporting illness, the decision on whether or not to seek health care is made. Third, conditional on the decision to seek treatment, the decision to choose a health care provider for treatment is made. Unlike Ellis and Mwabu (2004) who conceptualized these decisions as being simultaneously made, this study views the decisions as sequential. Thus, estimation is performed under the assumption that the error term in each decision stage is independent of the error

terms in subsequent decision stages, for example the error term of the decision to report illness or injury is independent of the error terms in health care and provider choice models.

For the first decision, a subjective measure of health status is used. Identification of an individual's health status is based on a question in the survey as to whether an individual was ill in the four weeks prior to the survey. This is a binary response health measure with two categories (1=good health, 0=bad health). The second decision on whether or not to seek health care conditional on reporting illness is also a binary response (1=sought care, 0=did not seek care).

Since decision one and two hinges on a notion of a latent variable, a binary response model is central to the analysis of the determinants of an individual's health status. The latent variables for the two decisions (reporting illness and seeking care conditional on illness) are linked to the observed binary variable using a measurement equation of the form:

$h_t = 1$ If $h_i^* \leq \tau$ for illness reporting, where h signifies ill reporting, and *tau* is a threshold unobserved health status; moreover, $d_i = 1$ if $d_i^* > \tau$ and $d_i = 0$ if $d_i^* > \tau$ for decision to seek health care...(9)

where, d signifies that the individual reported intention to seek care, and *tau* is a threshold intention to report such intention.

The latent variables h_i^* and d_i^* are assumed to be linearly related to the observed characteristics through the health production model of the form:

$$h_i^* = \mathbf{x}_i \beta + \varepsilon_i \dotfill (10)$$

Equation (10) is analogous to the model for decision to seek health care, which is omitted for brevity.

Assuming that ε_i is normally distributed, equation (10) leads to a probit model and the probability that individual i will report an illness can be expressed as:

$p_i = \Pr(h_i = 1 \mid \mathbf{x}_i)$ if $h_i = 1$ is observed

$1 - \Pr(h_i = 1 \mid \mathbf{x}_i)$ if $h_i = 0$ is observed $\dotfill (11)$

Following Green (2008), the probability density function for equation 11 can be expressed as:

Prob (h=1|x) = $\int_{-\infty}^{x_i} \varphi(t)dt = \varphi(x_i'\beta)$...(12)

In order to get the values of parameter vectors β, we invoke the maximum likelihood estimation (or the log-likelihood) technique. Since the observations are independent, the likelihood function is expressed as:

$$L(\beta \mid h, X) = \prod_{i=1}^{N} p_i \dotfill (13)$$

Combining equation (11) and (12) gives

$$L = \prod_{h=1} pr(h_i = 1 | \mathbf{x}_i) \prod_{h=1} [1 - pr(h_i = 1 | \mathbf{x}_i].\text{...}(14)$$

where the index for multiplication indicates that the product is taken over those cases where h=1 and h=0, respectively (Long, 1997). The same applies for the decision to seek or not to seek health care.

The third decision is the choice of health care provider conditional on reporting illness. The total numbers of alternatives are four and for purposes of analysis are numbered as: 1 for government facilities, 2 for private facilities, 3 for mission facilities, and 4 for others (self care). The probability function of choosing option j from among the choices in the health care is expressed as:

$$p_{ij} = \frac{\exp(\beta \mathbf{x}_{ij})}{\sum \exp(\beta \mathbf{x}_{ik})} \text{...}(15)$$

The likelihood function to be maximized is then given by:

$$L = \prod_{i=1}^{N} \prod_{j=1}^{j=4} P_{ij}^{Q_{ij}} \text{...}(16)$$

Equation (16) gives the β values that maximize the likelihood of observing the x's. However, in order to get the effect of the β on the probability of visiting provider *j*, marginal effects need to be computed.

We model only the first visit to the health provider and not the frequency of visits in order to avoid the effects of supplier induced demand. The model implies that the outcome categories are mutually exclusive, since a household cannot reveal a preference for two or more providers at the same time. In addition, we assume each household knows which health care facilities are available together with their prices and other associated attributes such as quality of care and the distances to be travelled to the facility.

The process that determines illness reporting is unlikely to be exogenous to health care choices. This indicates possibility of selectivity bias, when estimation of a model of facility choice is based on a sample of sick individuals. However, Dow (1995) using Cote d'ivoire data and Lindelow (2005) using Mozambique data, find that health demand estimates conditioned on health status do not suffer from statistical selectivity bias.

3.4 Data and Sources

The study uses primary data collected in 2007 through the Kenya Household Expenditure and Utilization Survey (KHHEUS) by the Kenya National Bureau of Statistics (KNBS) and the health ministries. The data covers the whole country and is nationally representative. As already noted, the survey was designed and

implemented by the Ministry of Health in collaboration with the KNBS during the last quarter of 2007. A nationally representative sample of 8,572 households with 35,460 individuals was selected for interviews on questions related to health; health care utilization for both inpatient and outpatient, as well as other related health services; mortality in the last one year preceding the survey; and access to health insurance. In addition, demographic and socio-economic variables were collected. In total, 737 sample clusters were covered with 506 and 231 being from the rural and urban areas, respectively. In each cluster, 12 households were systematically randomly selected from all provinces and districts.

The variables retained in the analytical sample for this study were chosen based on previous research on analyses of health and demand for health care. The health outcome variable is captured by the response to SAH question in the survey. Each individual in the household was asked the following question: 'Were you ill in the last four weeks prior to the survey?' Yes and No answers were the only options given. Conditional on reporting illness, the respondents were asked to state whether they consulted a health provider. The response to this question is the basis for constructing the outcome variable (the dependent variable) in the analysis of the decision to seek care. Conditional on reporting illness four weeks prior to the survey, and having reported on consulting a provider, the respondents were asked to state the specific health care providers they consulted. The response to this question is used to construct the dependent variable in the demand for health services at alternative sources of care; namely, government, private, mission and 'other' providers. The analysis is confined to the first visit made to the health care provider in the reference period.

The health status sample consists of 35,460 individuals but after dropping the observations with missing values, the final analytic sample consists of 35,342 individuals. The assumption in the analysis is that the mothers of the children aged below 16 years act as their agents in health care decision making (Bolin *et al.*, 2001). Out of the 4,473 individuals who reported to having been ill four weeks prior to the survey, 3,832 reported to have consulted a health care provider. Dropping the missing values leaves a final sample of 4,443 for analysis of the decision to seek health care. For the health care provider choice sub-sample, dropping the observations with missing values yields a sample size of 2,320 individuals. The observations dropped because the missing values are assumed to be selected out of the analytic sample randomly. Therefore, the final analytic samples for the three types of analyses contain variables with no missing values. STATA program version 10 is used for all the analyses performed.

3.5 Definition of Variables

Three dependent variables are defined for regression analyses, but the explanatory variables vary across the three regression models estimated. All the variables that appear in the regression models are shown in Table 3.1. The age variables include the linear term-Age and the quadratic term-Age squared, to permit for non-linearity in the health production function. The non-linear specification allows detection of variations in the health depreciation rate through the life cycle. As has been noted in literature, a priori signs for the variables listed below are ambiguous, and depend on country specific contexts. However, a priori sign for the cost of treatment and an individual's age is well agreed upon in literature. If the price of health care increases, the demand for health care decreases, implying a negative sign for the price coefficient. However, the signs on life cycle variables are ambiguous: health status may initially improve with age but decrease at later ages, implying deterioration in health as the individual ages.

Table 3.1: Variable definitions

Variable	Definition
Illness reporting	Dependent variable for reporting illness (1=reporting being sick in the past 30 days)
Seek treatment	Dependent variable for seeking treatment (1=sought treatment)
Health care provider	Dependent variable for choice of provider (1=government, 2=private, 3=mission, 4=other)
Gender	Male (=1)
Medical insurance	Does the individual have medical insurance? (1=yes)
Gender* insurance	Interaction between gender and insurance
Age	The age of the ill individual as at the last birthday (years)
Age squared	The age of the individual squared
Household size	Size of the household
Location	Location dummy (1=urban 0=rural)
Employment	Employment status dummy of the individual (1=employed)
Health stock	Whether the individual has a chronic illness (1=yes)
Mode of transport	The method of transportation to the health facility (1=walking)
Distance	Distance covered in kilometers to the facility (one way)
Cost of treatment	The cost of obtaining treatment from the provider, excluding transportation costs (Kenya shillings)
Years of schooling	The total number of years of schooling completed by each individual
Log of income	The log of household's income proxied by total consumption expenditure, Kenya shillings

4.   Findings and Discussions

4.1   Sample Statistics

Table 4.1 shows sample statistics for the study, that is the means, standard deviations as well as the maximum and minimum values of continuous and categorical variables.

In the sample, children aged less than one year were recorded as being 0 years old. The mean age of respondents in the overall sample is 24 years, and 51 per cent of them are females. This is an indication of a youthful population in the sample. This mean age is consistent with the age structure of the Kenyan population, which shows a youthful population (KNBS, 2009). In addition, the average household size in the sample is 5 persons, which compares to the national average (KNBS, 2009). The mean level of education is about 5 years, implying that majority of the people have gone up to the primary level of schooling, and 28.1 per cent of respondents are employed. Some persons pay for health services received, while others do not or pay low prices resulting in a mean care price of Ksh 309. Health insurance as a form prepayment mechanism for access to health care is available to about 7 per cent of the respondents. The minimum distance to a health provider is 0 kilometers, implying that on reporting an illness, some people administered self treatment at home, therefore they did not have to travel any distance to obtain care. However, the mean distance travelled to any health facility is 15 kilometers.

Table 4.1: Sample statistics

Variable	Mean	Std. Dev.	Min	Max
Gender (1=male)	0.49	0.50	0	1
Health insurance (1=Insured)	0.07	0.257	0	1
Gender*health insurance	0.04	0.19	0	1
Age (years)	23.76	18.98	0	110
Years of schooling	4.74	4.64	0	20
Location (1=urban)	0.26	0.44	0	1
Household size	5.47	2.37	1	14
Cost of treatment	309.84	2,216.334	0	100,000
Log of income	11.294	1.014	5.484	16.594
Distance	15.18	80.14	0	1,560
Mode of transport (1=walking)	0.59	0.49	0	1
Health stock (1=chronic illness)	0.05	0.22	0	1
Employment status (1=employed)	0.282	0.45	0	1

Source: Computed from KHHEUS (2007) data

Roughly, 6.9 per cent of the respondents have some form of health insurance. Of these, 15.7 per cent have private medical insurance, 13.2 per cent employer sponsored medical insurance, 69.6 per cent NHIF, while 0.6 per cent and 0.9 per cent have community and other forms of insurance, respectively. However, the proportion of individuals with any form of health insurance is a conservative estimate because insurance cover for some individuals, particularly household heads, is available for use by other household members.

Table 4.2 reports descriptive statistics on self reported morbidity rates. Approximately 12.6 per cent of the respondents were ill during the four weeks prior to the survey, with illness incidences being higher among lower income groups. People in rural areas tend to have a higher illness prevalence rate than those in the urban areas, with women reporting illness more frequently than men. Persons in wage employment report better health than the unemployed.

People in the 15-44 age group tend to report illness more often than the rest, with considerable variation across provinces. The most commonly reported ailments are malaria (40%) and diseases of the respiratory system (22%). Infants (0-4) have the highest incidence of diarrhea reporting (36.8%), while persons above the age of 16 report overwhelming cases of malaria symptoms (59.9%).

Table 4.3 shows that people in urban areas report a higher rate of health insurance coverage (15%) compared to those in rural areas (4%). The employed are more likely to report having a health insurance cover, compared with the unemployed. The age group 45-65 years has the highest frequency of having

Table 4.2: Self reported morbidity rates

Morbidity reports	No. of observations	%
Reported illness	4,473	12.6
Reported not ill	30,987	87.4
Morbidity by insurance		
Not insured	3,970	89
Insured	503	11
Morbidity by location		
Urban	1,324	30
Rural	3,149	70
Morbidity by gender		
Male	1,906	43
Female	2,567	57
Morbidity by employment status		
Employed	1,449	32
Not employed	3,023	68

Source: Computed from KHHEUS data, 2007

insurance coverage. It seems that those with insurance have less illness reporting rates (Table 4.2), probably due to their ability to access medical care on time since they do not have to make out of pocket payments at the time of illness. Persons above 65 years and infants have the lowest health insurance cover of 3 per cent and 1 per cent, respectively.

From the sample that reported being ill, 84 per cent sought formal or informal care. Of these, 56.9 per cent were women, while 43 per cent were men. The age group 15-44 reported seeking treatment more often (39%) conditional on reporting an illness, while the age group (over 65) had the lowest reported rate of seeking treatment (8%). The elderly reside mainly in the rural areas (88%), and this may explain why they do not seek care conditional on reporting illness, due to probably distance and cost factors associated with treatment.

4.2   Estimation Results

The estimations results for health production function are provided in Table 4.4. The table shows effects of various factors on the probability that a person randomly selected from the population will report having been ill over some reference period, in this case four weeks prior to the survey. In other words, Table 4.4 shows factors affecting the probability of reporting poor health. It is

Table 4.3: Variation in health insurance coverage by socio-economic characteristics

Characteristics	No. of observations	%
Insurance by gender		
Male	17,388	7.3
Female	18,072	6.5
Insurance by location		
Rural	26,131	4
Urban	9,329	15
Insurance by employment status		
Employed	9,986	14
Not employed	25,474	4
Insurance by age group		
0-4	4,855	1
14-15	9,333	2.7
15-44	15,696	10.4
45-65	4,079	11.7
over 65	1,457	3.1

Source: Computed from KHHEUS data, 2007

Table 4.4: Determinants of self reported health status: Dependent variable is probability of reporting illness (1=reported being sick four weeks prior to the survey)

Parameter estimates (Marginal effects)[a]			
Explanatory Variables	Linear Probability Model	Binary Logistic Model	Binary Probit Model
Gender	-0.0276*** (0.00430)	-0.0263*** (0.00428)	-0.0271*** (0.00436)
Insurance	0.0237* (0.0140)	0.0249* (0.0132)	0.0246* (0.0134)
Gender*Insurance	0.00354 (0.0182)	0.00458 (0.0161)	0.00292 (0.0166)
Age	-0.00242*** (0.000511)	-0.00168*** (0.000418)	-0.00189*** (0.000434)
Age squared * 10-2	0.00460*** (0.000704)	0.00302*** (0.000522)	0.00347*** (0.000555)
Years of schooling	-0.00396*** (0.000654)	-0.00425*** (0.000618)	-0.00423*** (0.000637)
Household size	-0.0130*** (0.000941)	-0.0133*** (0.00100)	-0.0135*** (0.00101)
Location (1=urban)	0.0185*** (0.00634)	0.0172*** (0.00613)	0.0178*** (0.00624)
Employment status (1=employed)	0.00938 (0.00596)	0.0114** (0.00578)	0.0113* (0.00590)
Health stock (1=chronic illness)	0.268*** (0.0141)	0.251*** (0.0146)	0.290*** (0.0143)
Log of income * 10-2	0.510** (0.250)	0.570** (0.242)	0.608** (0.249)
Constant	0.828*** (0.0273)		
Observations	35,342	35,342	35,342
R-squared	0.057		

Robust standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1;
[a]: All coefficients on dummies adjusted using the formula exp(betahat) − 1 (see Halvorsen and Palmquist (1980)

assumed that underlying poor health is associated with reporting of an illness over a reference period. The estimated coefficients show impacts of explanatory variables on the probability that an individual will report an illness; that is the probability that an individual is in poor health. A variable that reduces this probability is assumed to enhance health; that is to produce at least an additional unit of health. It is from this perspective that the estimated coefficients in Table 4.4 are interpretable as parameters of a health production function. Three

probabilistic models of self-reporting illnesses are estimated; namely, the linear, logit, and probit models. As can be seen from the table, the coefficients of the three models differ only slightly. However, theoretically, the linear probability model has the problem that its variance is heteroscedastic, and the predicted value of the probability of reporting illness can lie outside the unit-interval. Making an assumption on the error term will guide in the selection between logit and probit model. The preferred results are from the probit model (given as marginal effects), in which the error term is assumed to be normally distributed.

The dummy variables coefficients for the probit model are adjusted using the formula proposed by Halvorsen and Palmquist (1980) who show that the coefficients of the dummies should undergo further transformation before interpreting them.

It can be seen from the results in Table 4.4 that as an individual age increases, the probability of reporting good health increases. However, this probability of reporting good health decreases as the individual attains a certain age. The optimum age at which this is likely to happen is at 27 years, where an additional year on age increases probability of reporting illness. This is probably due to increased ability in recognizing a symptom or contracting age-old related diseases. Although age cannot be controlled by the individual in attempts to improve their health status, it is a variable that must be controlled for in determining the effects of other variables on health status. Men are less likely to report being ill than women in this sample. This does not necessarily imply that men are healthier, but that they are culturally more tolerant to disease, and probably report an illness when it is severe.

An additional member to a household reduces the probability of reporting good health ($p=0.0135$). This implies that the larger the household, the less likely they will report an illness if income per person is insufficient to cater for out-of-pocket payment required to treat random sickness. Since household members are aware of income scarcity, they might refrain from reporting an illness if it is conditioned on treatment seeking. Living in an urban area decreases the probability of having good health. This may be attributed to people in urban areas having a conscious perception of their health, and generally being more aware of the health care system, hence reporting worsening health conditions.

Income does have a systematic effect on the probability of reporting an illness. The coefficient of log of income is negative and significant ($p=-0.608$). This would probably imply that poor people are less likely to report illness. Income is a proxy for health inputs, implying that an extra unit in health inputs will decrease the probability of reporting illness. This shows that health inputs have a positive effect on health status. Having a medical insurance has a significant effect on

Table 4.5: Health effects of health insurance interacted with gender

Variable	Mean	Std. Dev.	Min	Max
Interaction effect	-.0029277	.0008948	-.0057239	-.0006399
Standard error	.0164788	.0050397	.0036	.0322363
z- Statistic	-.1776749	.000032	-.1777849	-.177384

illness reporting (p=-0.0240). If an individual has a medical insurance cover, the probability of reporting illness increases. Since health insurance proxies for medical care, people with insurance will tend to seek more health inputs through the use of medical care. This is because conditional on sickness; they intend to seek medical care. In the long run, they will be healthier. However, this does not necessary imply that those with no health insurance are not sick. Since they may not seek care conditional on reporting illness, they refrain from reporting that they are sick. In the long run, they tend to have worse health as they do not have any health inputs to improve on their health. Higher probabilities of reporting an illness are significantly associated with being female and having a chronic illness.

As noted earlier in the literature, the interaction effect cannot be evaluated simply by looking at the sign or statistical significance of the coefficient on the interaction term, if the model is non-linear. The cross derivatives are computed using the inteff command in STATA. Results of the interaction between gender and medical insurance status are presented in Table 4.5. Reporting an illness may depend on having medical insurance and the gender of the person covered by insurance (effect of the interaction between gender and insurance). The coefficient on the interaction between gender and insurance in Table 4.4 is statistically insignificant. The full interaction effects are shown in Appendix Figures 1 and 2. The overall interaction effect is negative but statistically insignificant.

Conditional on reporting an illness, one has to decide on whether or not to seek health care. The parameter estimates for the probability of reporting having sought medical treatment conditional on being ill are presented on Table 4.6.

Of the demographic variables, only age is statistically significant in the decision to seek health care. An additional year on age decreases the probability of seeking treatment (p=0.00118). Having a medical insurance cover increases the probability of seeking health care (p=0.0579). A unit increase in the log of household income increases the probability of seeking health care by 0.0335 (or by 3.35%). The higher the income, the more likely an individual will seek treatment. Since only a few people in the sample have health insurance (6.9%), income is what seems to be the major determinant of the likelihood of seeking medical care when ill. The results in Tables 4.5 and 4.6 show that the factors determining illness reporting are different from those that govern the decision to seek treatment.

Table4.6: Determinants of decision to seek health care: Dependent variable is probability of seeking health care conditional on reporting illness (1=sought care)

Parameter estimates (Marginal effects)[a]			
Explanatory			
Variables	Linear Probability Model	Binarya Logistic Model	Binarya Probit Model
Age	-0.00134***	-0.00113***	-0.00118***
	(0.000359)	(0.000287)	(0.000303)
Gender	-0.00653	-0.00610	-0.00489
	(0.0128)	(0.0126)	(0.0127)
Years of schooling	0.00104	0.000845	0.00100
	(0.00151)	(0.00150)	(0.00153)
Household size	-0.00323	-0.00328	-0.00329
	(0.00299)	(0.00283)	(0.00288)
Location	-0.0314*	-0.0307	-0.0309
	(0.0180)	(0.0203)	(0.0200)
Employment	0.0319**	0.0267*	0.0264*
	(0.0162)	(0.0141)	(0.0146)
Health stock	-0.0260	-0.0241	-0.0239
	(0.0183)	(0.0172)	(0.0175)
Health insurance (1= if covered)	0.0461**	0.0571***	0.0579***
	(0.0184)	(0.0194)	(0.0194)
Log of income	0.0362***	0.0341***	0.0335***
	(0.00884)	(0.00800)	(0.00810)
Constant	0.502***		
	(0.0939)		
Observations	4,443	4,443	4,443
R-squared	0.020		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
a: All coefficients on dummies are adjusted using the formula: exp (beta hat) − 1 (see Halvorsen and Palmquist, 1980).

The results in Table 4.7 are for choice of providers conditional on reporting illness. The effects on demand of the interaction between the variable of interest, insurance and gender, are captured in the model. To illustrate the effects of interaction terms, consider the interaction effects of two variables, x1 and x2. In this case, the demand effect of x1 is conditional on the level of x2. This conditional effect is equal to the sum of x1's "interactive" effect, through the term x1, x2, and its "main" effect through the term x1 alone (Friedrich, 1982). However, caution

should be exercised in the interpretation of the marginal effect of an interaction term, because it represents the effect of an independent variable holding all other variables constant. However, an interaction effect is generated by joint variation of the interacted variables, with the overall effect of x1 in this case being dependent on the level of x2, and the pure interactive effect of either x1 or x2 being the cross effect, that is, the cross partial derivative of the own partial derive of either variable.

The estimation results are interpreted with reference to the 'other' health care category, comprising traditional healers, chemists as well as self treatment. This is the comparison category, and will often be referred to as the self treatment option in the analysis.

Table 4.7: Multinomial probit estimates for choice of health care providers conditional on illness reporting

Explanatory Variables	Govt	Private	Mission	Other
Insurance(1=Insured)[a]	-0.0383 (0.0671)	0.1411** (0.0580)	-0.00804 (0.0283)	-0.0811** (0.0386)
Gender(1=Male)[a]	-0.0275 (0.0261)	0.0228 (0.0219)	-0.0206* (0.0124)	0.0256 (0.0210)
Insurance* Gender	-0.112 (0.0920)	-0.0246 (0.0594)	0.0606 (0.0689)	0.0762 (0.0810)
Age	-0.00135** (0.000658)	0.00126** (0.000545)	0.000336 (0.000289)	-0.000244 (0.000522)
Years of schooling	0.00460 (0.00308)	-0.00511** (0.00249)	-0.00199 (0.00153)	0.00250 (0.00239)
Location(1=Urban)[a]	-0.1722*** (0.0327)	0.1491*** (0.0290)	-0.000551 (0.0177)	0.0520* (0.0260)
Household size	0.00759 (0.00590)	0.00263 (0.00482)	-0.00269 (0.00278)	-0.00753 (0.00478)
Employment status(1=Employed)[a]	-0.0451 (0.0324)	0.00509 (0.0265)	-0.0258** (0.0132)	0.0684** (0.0268)
Cost of treatment * 10-3	-0.0133 (0.0250)	0.0412*** (0.0144)	0.0147*** (0.00557)	-0.0427* (0.0232)
Log of income	-0.0447*** (0.0160)	0.0265** (0.0132)	0.00578 (0.00743)	0.0124 (0.0122)
Distance *10-2	-0.0275* (0.0151)	0.0228** (0.0110)	0.0101** (0.00493)	-0.00543 (0.0135)
Transport mode (1=walking)[a]	-0.1263*** (0.0259)	0.0217 (0.0204)	-0.0255* (0.0136)	0.1491*** (0.0195)
Observations	2,320	2,320	2,320	2,320

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[a]: All coefficients on dummies for significant variables adjusted using the formula exp (beta hat) – 1 (see Halvorsen and Palmquist, 1980).

The focus of Table 4.7 is to measure the effect of insurance coverage on choice of treatment options controlling for impacts of other factors that affect treatment choices such as socio-economic and demographic variables. The estimation results show that increasing health insurance coverage decreases the probability of demand for care at a government facility, while increasing demand at a private facility. In particular, a 10 per cent increase in insurance coverage would raise the probability of attending a private clinic by 1.41 per cent. In addition, it would decrease the probability of self treatment by 0.81 per cent.

The coefficient on interaction of insurance and gender is not statistically significant. However, the signs on the coefficients indicate that controlling for all other factors, men who have insurance are less likely to seek health care in government and private health facilities relative to women. However, as noted in the literature, the marginal effects shown in the table do not indicate the correct interaction effect of gender with insurance on provider choice probabilities. At present, in contrast to binary case (see Table 4.5), there is no STATA command or command from any other statistical software that can compute the correct interaction effects for a multinomial probit model. However, manual computations of interaction effects in a multinomial probit are feasible (King, 2000), but efforts in this direction for this study were not fruitful.

User fees are expected to reduce the demand for consultations at various health care providers. This study finds that if user fees were to rise, the probability of consultations at private and mission clinics would increase. The positive sign on user fees (cost of treatment) is contrary to predictions of demand theory. This finding could be due to a positive correlation between user fees and quality of care. A 10 per cent increase in income would decrease the probability of consulting a government provider by 0.45 per cent, but increase consultation probability at a private provider by 0.27 per cent.

As an individual grows older, the probability of visiting government facilities decreases, while that of consulting private provider increases. A year of schooling reduces the probability of a visit to a private clinic by 0.511 per cent. This may be because as people's literacy level improve, they are able to determine which medical care would improve their health best, especially in an event of a serious illness, which is cheaper to treat in a government health facility. Being employed decreases the probability of consulting a mission health care provider by 2.6 per cent, while increasing that of self treatment by 6.8 per cent. This is probably because the opportunity cost of time is high when one is employed and so people will seek treatment options that are less time consuming such as purchasing drugs for self treatment at pharmacies.

Living in an urban area decreases the probability of visiting a government health provider by 17 per cent, but increases that of visiting private health care and self treatment by 15 per cent and 5.2 per cent, respectively. This implies that the probability of self treatment for people living in urban areas is 17 percentage points higher than for rural areas. Moreover, being in an urban area increases the probability of self treatment by 5.2 per cent. This means that in the event of illness, people in urban areas are less likely to visit a formal health care provider relative to rural residents. Walking to a health facility is associated with a disutility. Walking reduces the probability of visiting government and mission health facilities, but is associated with an increase in probability of a visit to private clinics. In addition, an increase in distance to health facilities decreases the probability of people visiting the government providers, but increases probabilities of visiting private and mission providers.

4.3   Simulation Results

Estimation results in Table 4.7 are used to simulate effects of various public policies on health care demand in government and non government facilities. In particular, the effect of increasing health insurance coverage on visit probabilities at various health facilities is simulated. From my sample, the coverage for all forms of medical insurance is about 7 per cent, implying a 94 per cent increase in coverage is required for universal health insurance to be realized. There are many mechanisms of achieving this goal.

Demand effects of policy changes associated with different levels of medical insurance coverage, up to full coverage, are examined. Table 4.8 shows the new choice probabilities and changes in base probabilities upon implementation of policy measures that can increase insurance coverage. In Table 4.8, sample proportions are those of the study sample that selected each treatment option. The base probabilities are the proportions of the sample predicted to select each option based on estimation results in Table 4.7. As can be seen from a comparison of base and sample probabilities, the estimated multinomial probit model does not perfectly predict treatment choice probabilities. In particular, the model over-predicts the selection probability for government, private and mission facilities, and under-estimates self treatment.

It can be seen from the table that if medical insurance coverage was to increase from the current 6 per cent to 20 per cent, the choice probability of consulting government health facilities would decline from 0.521 to 0.515. This implies an absolute decline of 0.5 per cent of the share of persons consulting government facilities. Likewise, the probability of consultation at the mission and other

providers would fall in absolute terms by 0.1 per cent and 1.1 per cent, respectively. On the contrary, this policy measure increases the probability of consulting with private health care facilities by 1.9 per cent in absolute value, from 20 per cent to 22 per cent. This reduction would divert the demand to private providers. This is especially good for those who self treat as they are now able to access proper health care as opposed to self treatment. Increasing insurance coverage to 100 per cent will decrease the choice probability for government clinics to 0.485, an absolute decline of 7.0 per cent. However, reductions in consultation probabilities would be 36.3 per cent and 11.6 per cent for self treating and mission clinics, respectively. In contrast, the choice probability for private clinics increases significantly in absolute terms by 65.3 per cent.

As can be seen from the simulations table, the choice probabilities of consulting government clinics are declining as health insurance coverage increases. The same is for mission and self treatment. However, it is noteworthy that even with a large increase in insurance coverage; the decrease in choice probabilities for government facilities is not as large as expected. The government would still remain the main important source of medical care for the population even when everyone is fully covered by health insurance.

It should also be noted that whether 6 per cent of the people have medical insurance or 30 per cent of the population is covered, the proportion of patients predicted to visit a particular health facility is not affected. The reason is the estimated coefficient on health insurance (the demand effect of insurance) is independent of the sample proportion covered by health insurance.

The last column of Table 4.7 compares arc elasticities of health care demand at government, private and mission facilities as well as self treatment option. The demand elasticities show the sensitivity of visit probabilities for each provider to a change in the proportion of the sample covered by health insurance. The elasticity of demand with respect to insurance is largest for the self treatment option, and smallest for private health facilities. In particular, a 1 per cent increase in insurance coverage reduces the demand for health care at government facilities by only 0.0044 per cent but decreases for self treatment by 2.3 per cent. However, the percentage change in demand may be understated because the elasticities shown in the table are computed at very low levels of health insurance coverage, which greatly exaggerates the proportional change insurance coverage. In overall terms, consultation probabilities at all sources of care are highly inelastic with respect to change in the proportion of the sample covered by health insurance coverage.

Table 4.8: Policy simulations and responsiveness of consultation probabilities to insurance coverage

	Probability of seeking			
	Government	Private	Mission	Self
Sample proportions	0.427	0.166	0.053	0.354
Base probabilities	0.521	0.203	0.0656	0.210
Policy intervention: increasing medical insurance coverage from 6-20%				
Change in base	-0.005	0.020	-0.001	-0.011
Simulated probabilities	0.516	0.223	0.064	0.199
Relative change in base probabilities (%)	-1.03	9.73	-1.72	-5.4
Policy intervention: increase health insurance coverage from 6-40%				
Change in base	-0.013	0.048	-0.003	-0.028
Simulated probabilities	0.508	0.251	0.063	0.183
Relative change in base probabilities (%)	-2.5	23.6	-4.2	-13.1
Policy intervention: increase health insurance coverage from 6-60%				
Change in base	-0.021	0.076	-0.004	-0.044
Simulated probabilities	0.500	0.280	0.061	0.167
Relative change in base probabilities (%)	-4	37.5	-6.6	-20.8
Policy intervention: increase health insurance coverage from 6-80%				
Change in base	-0.028	0.104	-0.006	-0.060
Simulated probabilities	0.493	0.307	0.059	0.150
Relative change in base probabilities (%)	-5.4	51.4	-9.1	-71.5
Policy intervention: increase health insurance coverage from 6-100%				
Change in base	-0.036	0.133	-0.008	-0.076
Simulated probabilities	0.485	0.336	0.058	0.134
Relative change in base probabilities (%)	-7	65.3	-11.6	-36.3
Elasticity of demand with respect to health insurance coverage	-0.004	0.000043	-0.0074	-0.0232

Source: Author's computation

5. Conclusion, Policy Implications and Recommendations

5.1 Conclusion

The purpose of the study was to examine the demand for health care in Kenya, with specific emphasis on the role health insurance plays in the production of health and in influencing demand for health care. This was done by treating a household member as a producer of health for self or other household's members. This was followed by modeling the probability of seeking treatment conditional on reporting an illness. Finally, a model of the probability of choosing a particular health care provider was formulated and estimated. By separately modeling the probability of reporting illness from that of seeking treatment, a better understanding of health care seeking behaviour is facilitated. In addition, factors responsible for self reported health status can be identified and used to inform health care policy making.

The findings of the study show that the effects of the demographic variables are more important in influencing the probability of illness reporting than in affecting the probability of seeking care. Women are more likely to report an illness and seek care than men, while large households report illness less frequently than small families. People with higher incomes and insurance are more likely to report an illness and seek treatment compared to those without insurance.

Health insurance, gender, income, distance and mode of transport to a health facility strongly influence the choice of a health provider. The probability of visiting government facilities is lowered by having insurance. However, it increases with income and decreases with distance. Walking is positively associated with probability of self treatment and negatively correlated with probability of visiting government facilities. An increase in the cost of treatment is associated with increased probabilities of consulting private and mission providers, possibly due to correlation of quality of care with its price.

A policy intervention aimed at increasing health insurance coverage will decrease the probability of consulting a government facility, mission and self treatment, while increasing that of visiting private facilities. However, these probabilities respond inelastically to changes in insurance coverage.

5.2   Policy Implications

The diversion of demand still leaves the government as the largest heath provider. This implies that more resources will be required if quality health care is to be provided to this population. In addition, for utilization to increase by a small amount, a very large increase in health insurance coverage is required. This means that the cost of achieving this universal coverage will be immense for the government. With majority of the population being poor, the government will have to provide for their insurance, in addition to ensuring adequate health care at every government health facility. This means the financial resources of the government will be overstretched.

Health insurance can potentially improve the population health. However, the increased demand for medical care by those with a health insurance cover would also imply an indication of moral hazard. This is a situation where people may actually demand for more health care than they need leading to escalated costs of health care, which may increase premiums so as to cater for the unnecessary rise in health care demand.

Reduction in cost of health care at the point of utilization through provision of universal coverage does not provide the expected increase in utilization rates. Other factors such as the non monetary costs involved in health care provision may explain how the utilization of health care can increase. These are factors like distance to the health facilities, quality of service offered, and waiting time at the health facilities.

5.3   Policy Recommendations

This study recommends that health insurance is provided to women as it is one avenue of increasing their access to health care, leading to improvement in their health as well as that of their children. This is because women act as agents of their children.

References

Ai, C. and Norton E. C. (2003), "Interaction Terms in Logit and Probit Models," *Economics Letters*, 80(1):123-129.

Akin, J.S., Griffin, C., Guilkey, D.K. and Popkins, B.M. (1986), "Demand for Primary Health Services in the Bicol Region of Philippines," *Economic Development and Cultural Change*, 34(4): 755-782.

Arrow, K. J. (1963), "Uncertainty and the Welfare Economics of Medical Care," *American Economic Review*, 53(5): 941-973.

Becker, G. S. (1965), "A Theory of the Allocation of Time", *The Economic Journal*, 75(299):493–517.

Bedi A. S., Kimalu P., Kimenyi M. S., Manda D. K. , Mwabu G. and Nafula N. (2004), "User Charges and Utilisation of Health Dervices in Kenya, KIPRRA Discussion Paper No. 32, Nairobi: KIPPRA.

Berry, W., DeMeritt, J. H. and Esarey, J. (2010), "Testing for Interaction in Binary Logit and Probit Models: Is a Product Term Essential?"*American Journal of Political Science*, 54 (1):248-266.

Bichaka, F. and Paulos, G. (2008), *A Health Production Function for Sub- Saharan Africa*, Middle Tennessee State University and Institute of Development Research, Addis Ababa University, Unpublished mimeo processed.

Bolin, K., Jacobson, L., and Lindgren, B. (2001), "The Family as the Producer of Health-When Spouses are Nash Bargainers," *Journal of Health Economics*, 20: 349–362.

Brambor, T., Clark, W. R. and Golder, M. (2005), "Understanding Interaction Models: Improving Empirical Analyses," *Political Analysis* 13:1-20.

Cameron, A. C., Trivedi, P. K., Milne, F. and Piggott, J. (1988), "A Micro-econometric Model of Demand for Health Care and Health Insurance in Australia," *Review of Economic Studies*, 55(1): 55-106.

Card, D., Dobkin, C. and Maestas, N. (2008), "The Impact of Nearly Universal Insurance Coverage on Health Care Utilization and Health: Evidence from Medicare," *American Economic Review*, 98(5): 2,242–2,258.

Chen, L., Yip, W., Chang, M., Lin, H., Lee, S., Chiu, Y. and Lin, Y. (2007), "The Effects of Taiwan's National Health Insurance on Access and Health Status of the Elderly," *Health Economics*, 16(3): 223–242.

Desai, S. (1987),"The Estimation of the Health Production Function for Low Income Working Men," *Medical Care*, 25(7):604–615.

Dow, W. H. (1995), "Unconditional Demand for Curative Health Inputs: Does Selection on Health Status Matter in the Long Run?" Rand Labour and Population Program, Working Paper Series 95-22.

Ellis, R. P. (1987), 'The Revenue Generating Potential of User Fees in Kenyan Government Health Facilities," *Social Science and Medicine*, 25(9):995–1,002.

Ellis, R. P. and Mwabu, G. (2004), "The Demand for Outpatient Medical Care in Rural Kenya," Boston University and University of Nairobi, Unpublished.

Franks, P., Clancy, C. M., Gold, M. R. and Nutting, P. A. (1993), "Health Insurance and Subjective Health Status: Data from the 1987 National Medical Expenditure Survey," *American Journal of Public Health*, 83: 1,295–1,299.

Franzini, L., Caughy, M., Spears, W. and Esquer, M. (2005), "Neighborhood Economic Conditions, Social Processes and Self Assessed Health in Low-Income Neighborhoods in Texas: A Multilevel Latent Variables Model," *Social Science and Medicine*, 61(6): 788–804.

Friedrich, R. J. (1982), "In Defense of Multiplicative Terms in Multiple Regression Equations," *American Journal of Political Science*, 26 (4): 797-833.

Gertler, P. and Van der Gaag, J. (1990), "The Willingness to Pay for Medical Care: Evidence for Two Developing Countries," John Hopkins University Press, Baltimore.

Glick, P., Jean, R. and Iarivony, R. (2000), "Education and Health Services in Madagascar: Utilization Patterns and Demand Determinants," Cornell University, Unpublished mimeo processed.

Government of Kenya (2007),"Kenya Vision 2030," Nairobi: Ministry of Planning and Development.

Green, W. (2010), "Testing Hypotheses about Interaction Terms in Nonlinear Models," *Economics Letters*, 107: 291–296.

Green, W. (2008), Econometric Analysis, USA: Pearson Education, Inc.

Grossman, M. (1972a), "On the Concept of Human Capital and the Demand for Health," *Journal of Political Economy*, 80(2): 223-55.

Grossman, M. (1972b) "The Demand for Health: A Theoretical and Empirical Investigation," National Bureau of Economic Research Occasional Paper 119, New York: Columbia University Press.

Hadley, J. (2003), "Sicker and Poorer–The Consequences of Being Uninsured: A Review of the Research on the Relationship between Health Insurance, Medical Care Use, Health, Work and Income," *Medical Care Research and Review*, 60(2 supp): 3S–75S.

Hadley, J. and Waidmann, T. (2006), "Health Insurance and Health at Age 65: Implications for Medical Care Spending on New Medicare Beneficiaries," *Health Services Research*, 41(2): 429–451.

Halvorsen, R. and Palmquist, R. (1980), "The Interpretation of Dummy Variables in Semi-logarithmic Equations," *The American Economic Review*, 70(3):474-475.

Hong, W., Licheng, Z., William, C. H. and Winnie, Y. (2009), "The Impact of Rural Mutual Health Care on Health Status: Evaluation of a Social Experiment in Rural China," *Health Economics*, 18:565-582.

Idler, E. and Benyamini, Y. (1997), "Self-Rated Health and Mortality: AReview of Twenty-Seven Community Studies," *Journal of Health and Social Behavior,* 38(1): 21–37.

International Finance Corporation (2006), "Section 1-The Role and Likely Evolution of the Private Sector in Health Care in Sub-Saharan Africa," The Business of Health in Africa.

Kaplan, G., Elsie R. P., Lynch, J. M., Richard, D. Cohen and Jennifer, L. B. (1996), "Inequality in Income and Mortality in the United States: Analysis of Mortality and Potential Pathways," *British Medical Journal*, 312: 999—1003.

Kenya Healthcare Federation (2009), "Status of Health Care Delivery in Kenya," Baseline Study on Healthcare Delivery in Kenya.

Kenya National Bureau of Statistics (2005/2006), *Kenya Integrated Household and Budget Survey*, Nairobi.

Kenya National Bureau of Statistics (2009), *Population and Housing Census Report*, Nairobi.

Leibowitz, A. A. (2004), "The Demand for Health and Health Concerns After 30 Years," *Journal of Health Economics*, 23: 663–671.

Levy, H. and Meltzer, D. (2001), "What Do We Really Know about Whether Health Insurance Affects Health?" Economic Research Initiative on the Uninsured, University of Michigan.

Lindeboom, M. and van Doorslaer, E. (2004),"Cut-Point Shift and Index Shift in Self-Reported Health", *Journal of Health Economics* 23(6): 1083–1099.

Lindelow, M. (2005), "The Utilization of Curative Health Care in Mozambique: Does Income Matter?"*Journal of African Economies*, 14(3): 435-482.

Long, J. S. (1997), Regression Models for Categorical and Limited Dependent Variables, California, USA: Sage publications Inc. Thousand Oaks.

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., Leibowitz, A. and Marquis, M. S. (1987), "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment," *American Economic Review*, 77(3): 251-277.

Mankiw, G. N. (1998), Principles of Economics, The Dryden Press, Harcourt Brace College Publishers.

Mathers, C. D., Ezzati, M., Lopez, A. D., Januson, D. T. and Murray J. L. C. (2006), "Global Burden of Disease and Risk Factors," Washington DC: Oxford University Press.

McWilliams M., Zaslavsky, A., Meara, E. and Ayanian, J. Z. (2004), "Health Insurance Coverage and Mortality among the Near-Elderly," *Health Affairs*, 23(4): 223–233.

Meng-Kin, L. (2004), "Shifting the Burden of Health Care Finance: A Case Study of Public-Private Partnership in Singapore," *Health Policy*, 69(1): 83–92.

Mullahy, J. (2010), "Understanding the Production of Population Health and the Role of Paying for Population Health," *Public Health Research, Practice and Policy*, 7(5):A95.

Mwabu, G. M., Ainsworth, M. and Nyamate, A. (1993),"Quality of Medical Care and Choice of Medical Treatment in Kenya: An Empirical Analysis," *Journal of Human Resources*, 28(4):837-862.

Mwabu, G. M. and Wang'ombe, J. (1997), "Health Services Pricing Reforms in Kenya, 1989-1993," International Health Policy Program, Washington, DC: The World Bank.

Nagler, J. (1991),"The Effect of Registration Laws and Education on U.S. Voter Turnout," *The American Political Science Review*, 85(4):1393-1405.

Ngugi, R. (1999), "Health Seeking Behavior in the Reform Process for Rural Households: The Case of Mwea Division, Kirinyaga District, Kenya," AERC Research Paper 95.

Norton, E. C.,Wang, H. and Ai C. (2004), "Computing Interaction Effects and Standard Errors in Logit and Probit Models," *The Stata Journal* 4: 154-167.

Ntembe, A. N. (2009), "User charges and Health care provider choice in Cameroon," *International Review of Business Research Papers*, 5(6): 33-49.

Phelps, C. E. (1992), Health Economics, New York: Harper Collins Publishers.

Sen, A. (1998), "Mortality as an Indicator of Economic Success and Failure," *Economic Journal*, 108(446): 1–25.

Subramanian, S. V., Tim, H. and Mauricio, A. (2010), "Self-Reported Health Assessments in the 2002 World HealthSurvey: How do they Correlate with Education?" *Bull* 131, *World Health Organ*, 88:131–138.

Thomas, D. and Frankenberg, E. (2000), "The Measurement and Interpretation of Health in Social Surveys," Labor and Population Program, Rand Corporation, Working Paper 01-06.

World Health Organization (2007), Fact Sheet.

World Health Organization (2008), "Primary Health Care: Now More Than Ever," The World Health Report, Geneva.

Appendix

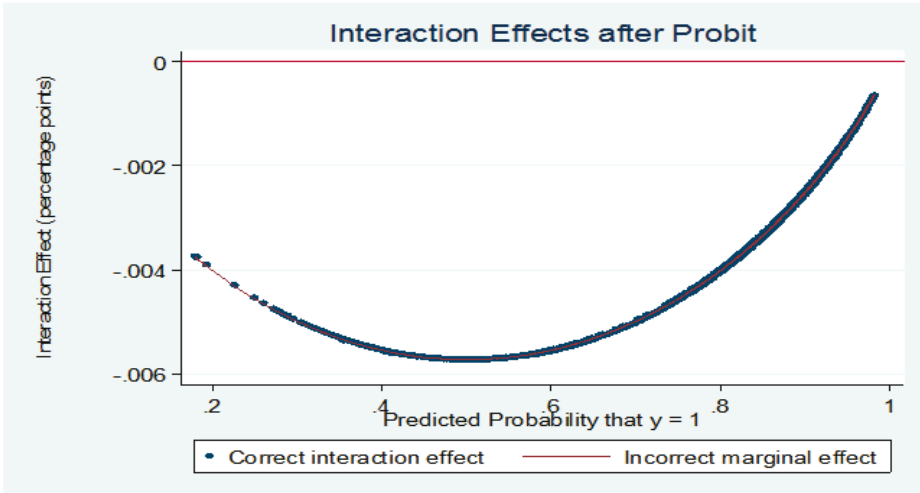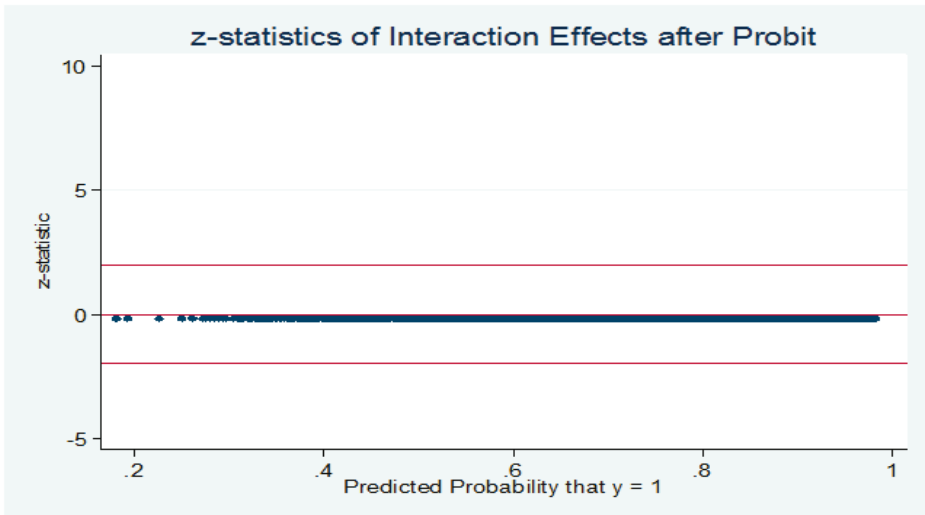### Figure 1: Interaction effects

Figure 2: Z—statistics after probit