Moses Kinyanjui Muriithi

THE DEMAND FOR HEALTH CARE IN A NAIROBI SLUM:

THE ROLE OF QUALITY AND INFORMATION

European Scientific Institute

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Moses KINYANJUI MURIITH

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CHAPTER ONE: HEALTH CARE DEMAND AND HEALTH CARE SYSTEM IN KENYA

1.1. Introduction: Health Care Demand

The term demand side appears with increasing frequency in health planning and policy literature. In the African region, health care demand analysis in this literature has been conducted in the context of economic and institutional transformations of national health sectors, particularly the marketisation of health care, and the emergence of provider pluralism, the collapse of public sector services, and the governance and regulatory failures (Standing, 2004, Janet et al,994).

There is a growing recognition that the African state cannot continue to fund the comprehensive range of services that it has traditionally provided. Due to the partial withdraw of the state from the social sector in sub-Saharan Africa, there has been an increase in pluralism of health care provision in recent years, most noticeably in the urban areas. Much of the pharmaceutical in Africa sector is now on private orientation, and the health specialists on the content are permitted to engage in private practice as is the practice in most other developing regions.

The World Bank (2004) avers that developing countries, especially in sub-Saharan Africa, continue to face a huge burden of disease due to poor nutrition, poor shelters, poor handling of water and waste, and inadequate preventive healthcare. The occurrence of illness can result in household welfare loss through increased spending on health or reduced labor productivity. Ill-health is cited as the most frequent and main cause and consequence of poverty. Martin and Haddad (2006) argue that in developing countries, some communities, regions and segments of the population are particularly disadvantaged in terms of access to public resources, and the availability of such resources may contribute to the development of health disparities. It is not surprising therefore that quality health care provision is one of the priorities of the many governments

It has been argued that the government efforts to address the challenges facing the health sector have been biased towards the supply side in most countries. For example the introduction

of more devolved funds in Kenya in the name of Constituency Development Fund (CDF) has witnessed emergence of many health centers, which suggests that people at the grassroots have identified their health care need as a key issue in poverty eradication efforts (Kamau and Muriithi, 2006). However, there is need to think beyond supply side issues, and consider how individuals behave during episodes of illness with a focus on the nature and range of the factors affecting their health seeking behavior, especially the economically vulnerable groups (see Feldstein,1966; WHO,2002). In urban areas, the slum households are among the most venerable social groups due to poor nature of social amenities provision in slums. Understanding the demand side of the health and health care in slums should guide health policy makers in formulating disease treatment and prevention policies that are area specific and effective. Further, understanding the underlying process of the demand for health care is essential for a better assessment of the role of public and private interventions in improving population health (see Fosu 1989). The following section provides a review of health status Kenya since independence.

1.2 Indicators of Health Status in Kenya

The health status of the population can be assessed by a number of indicators including the infant, child and maternal mortality and morbity rates; crude death rate; life expectancy at birth; and the number of medical staff and facilities available per unit of the population. These are the basic indicators of a country's health, socio-economic situation and the quality of life. The population of Kenya was estimated to be 37 million in 2007 while life expectancy was estimated to be 54.3 and 59.1 years for males and females, respectively (Republic of Kenya, 2007a).

The health achievements between 1963 and 1991 were encouraging. Infant mortality rate dropped from 126 to 52 per 1000 live births and the under five mortality rates dropped from 211 to 75 per 1000 live births. In the same period, life expectancy at birth, the number of years a new born infant would live if prevailing factors of mortality at the time of birth were to stay the same throughout the child's life rose from 40 to 60 years. The crude death rate dropped from 20 per 1000 at independence to 12 per 1000 in 1993 and the crude birth rate from 50 per 1000 to 46 per 1000 over the same period.

Although the health situation in Kenya improved progressively between 1963 and 1992, there appears to have been a reversal in the direction of change in the health status of the population in 1990s as reflected by the increase in morbidity and mortality.

The Kenya Human Development Report, UNDP (1999), noted that the positive gains that Kenya had achieved in reducing mortality rates between 1960 and 1992 were being eroded. This was confirmed in the 1998 Kenya Demographic Health Survey report (Republic of Kenya, 2003) which showed that infant mortality rate had gone up from 51 per 100 live births in 1992 to 74 per 100 live births in 1998. The under five-mortality rate had shot up from 74 in 1992 to 90 in 1995 and to 112 in 1998. This is surprising as a significant portion of the gains made during the first 25 years of independence was rapidly eroded in just a few years (Kimalu, 2001). The underlying factors in this reversal of health gains may include: deterioration in the quality and quantity of health services; the reduced access to service by the poor following the introduction of user fees; an overall decline in food availability and nutrition; decreased immunization coverage.

Maternal mortality related to pregnancy or childbirth complications is high. A 2003 report estimated maternal mortality at 414 per 100,000 live births (Republic of Kenya, 2003). Only 40 percent of deliveries are performed in a health facility. Overall, malaria, respiratory diseases, diarrhea diseases, skin infection, and intestinal worms are the commonest causes of illness, accounting for about 70 percent of all outpatient morbidity. This pattern has persisted during the past decade. Poverty has declined from 56 percent in 1990s to 46 percent in 2006 (Republic of Kenya, 2007). The national coverage of nurses is 120 nurses per 100,000 populations while that of medical doctors is 15 per 100,000 populations(Republic of Kenya 2007b)

The greatest challenge to independent Kenya has been the emergence of the HIV/AIDS pandemic. It is estimated that 2.2million Kenyans are now living with HIV infection, representing about 14 percent of the sexually active population. Over1.5 million Kenyans have died of AIDS since the epidemic started. The HIV/AIDS pandemic is more than a health problem as it affects economic,social, and cultural dimensions of society. The epidemic continues to exert great pressure on the healthcare delivery systems. Although there has been a massive expansion of health infrastructure since independence, increasing population and growth in demand for

health care has adversely affected the ability of the government to provide effective health services.

1.3 The Kenya HealthCare System

The health care system in Kenya is organized in a pyramidal pattern, from the dispensaries and health centers at the base of the pyramid, through sub-district hospitals and provincial general hospital and at the apex, referral hospitals (Mwabu, 1989). The health centers generally provide preventive and curative services while the dispensaries act as the health system's first line of contact with patients, providing a wider range of preventive health measures, which is a primary goal of Kenya health policy. The district hospitals oversee the implementation of health policy at district level, maintaining quality standards, and coordinating and controlling all district health activities. The national referral hospital provides sophisticated diagnostic, therapeutic and rehabilitative services. The two national referral hospitals are Kenyatta National Hospital in Nairobi and the Moi Referral and Teaching Hospitals at Eldoret. The provincial hospitals act as referral centres to support the district hospitals, providing highly specialized care.

The government health services are supplemented by privately owned and operated hospitals and clinics, and FBO hospitals and clinic. The mission health facilities are mainly located in the rural areas and some parts of urban areas that are not well served with private and public health facilities like slum environment. Private hospital and clinics operate for profit services. Their private health-care delivery systems include pharmaceutical outlets and community pharmacies distributed countrywide.

The health sector has been implementing a sector-wide approach to health care, which was initiated in 2005 to coordinate and harmonize the efforts of the government, development partners, and all other stakeholders in the health sector using one common sector strategy called National Health Sector Strategy Plan. If this new strategy is to have impact on health of the urban population, demand behavior of the urban population needs to be understood, especially slum areas.

1.4 Patterns and Distribution of Health Facilities

Kenya's health system is pluralistic, with a wide range of players, including the Ministry of Health and parastatal organizations and private sector, consisting of private for-profit, Non-Governmental Organizations and Faith Based Organization facilities. The MoH, operating a national wide system of health faculties, is the largest financier of health-care services in the country. The health services are provided through a network of over 4700 health facilities countrywide, with the public sector system accounting for about 52% of the health facilities in the country. The private sector, mission organizations and the ministry of local government run the remaining 48% of such facilities. The NGO sector predominantly provides health clinics, and maternity and nursing homes, with medical centres accounting for 85% of such facilities.

The development and expansion of health care services and facilities in terms of spatial coverage, training of personnel, and tertiary health care delivery services since independence has been commendable. Though the physical infrastructure for health provision in Kenya has expanded rapidly, distribution and coverage remains uneven especially in rural areas.

Table1.1: Distribution of public health facilities by province

Facility type	central	Coast	Eastern	Nairobi	North Eastern	Nyanza	Rift valley	Western	total
dispensaries	205	144	325	18	43	180	540	81	1,536
health centres	57	33	58	8	6	80	136	62	440
district hospital	12	11	26	1	10	24	21	13	118
provincial hospital	1	1	2	0	1	1	1	1	8
national and specialized hospitals	1		2						3
Rural Health and specialized centres	1	15	7		5	6	12	7	
total facilities	227	204	420	27	65	291	710	164	2,158
facilities %	12.8%	9.5%	19.5%	1.3%	3.0%	13.5%	32.9%	7.6%	100%
population	3,918,538	2,860,649	5,180,139	2,656,997	1,235,592	4,862,010	8,077,517	3,954,081	32,745,523
population per facility	14,146	14,023	12,334	98,407	19,009	16,708	11,377	24,110	15,174

Source: Public Expenditure Tracking Survey 2008

The above table shows that four provinces that is, Central, Coast, Eastern and Rift valley have lower than country's average population per facility of 15,174 as compared to the rest of the province with higher above country's average population per facility. Rift valley, which has a wide geographical coverage and highest population of about 8million people, has the highest number of health facilities. The table indicates that rift valley is better served than other provinces as it has a facility to population ratio of 1:11,377 followed by Eastern province with the ratio standing at 1:12,334, while Nairobi is the worst served with population per facility standing at 1:98,009.It should be noted that Nairobi's poor showing is due to the fact that the majority of the facilities are privately owned. Western Province is the second poorest, with

facility population ration of 1:24,110 followed by North Eastern Province with facility population ratio of 1:19,009.

1.5 Health Service Utilization Patterns

Since independence in 1963, Kenya has continued to design and implement policies aimed at promoting coverage of and access to modern healthcare in an attempt to attain the long-term objectives of health for all. On attaining independence, Government committed itself to providing free health services as part of its development strategy to alleviate poverty and improve the welfare and productivity of the nation.

Information on the utilization of both out-patient and inpatient health care is useful for monitoring patterns of care as a key part of health care system as well as for describing health conditions in the population. This information also permits a fuller understanding of access to health care with respect to both inpatient and outpatient health services. Barrier to care that is associated with differences in health care utilization may be more significant than barriers that do not affect utilization patterns. Besides access to care, health care utilization is strongly affected by care need and patient preferences and values.

The Household Health Expenditure and Utilization Survey report of 2007 indicated that urban areas tend to have a higher outpatient visits (3.1) per capita compared with their rural counterparts (2.5). This trend can be explained by the fact that urban populations have readier access to health care because they need to travel shorter distances and they are likely to have greater financial resources, and thus can afford higher levels of use. The report indicates further that women make 1.3 times as many visits per capita as males do. The young and the old make significantly more visits than those of intermediate age, thus yielding the popular J-curve on health consumption trend consistent with National Transfer Account (Manson et al, 2009). This implies that the very young and the elderly are more likely to be ill than those of intermediate age. In addition, children under the age of four have the highest rate of preventive visits.

Between 2003 and 2007, Kenya instituted a package of programs intended to improve access to medical services by providing free care. During this period free visits increased from 8 percent to 12 percent of all visits. Children were most affected by changes between 2003 and 2007. Nearly a third of the visits by the youngest children were free compared with 10-15

percent of visits in 2003. In 2003, the poor were significantly more likely than the rich to let an illness go untreated. By 2007, this gap had been reduced. Reduction in user fees at the lower levels ofpublic health facilities and the provision of drugs has led to increased utilization of medical services, especially among the poor. Although children were the main beneficiaries of free care, the increase in utilization was highest amongst adults, elderly.

In 2007, government facilities accounted for 57 percent of total outpatients visits. About 15 percent of visits were to chemists. Private and mission health facilities accounted for 18 percent and 16 percents of outpatient visits, respectively, while traditional healers attracted a negligible proportion (1 percent) of patients.

Table1.2: Visits to providers by provinces, 2007(percent)

Province	Public	private	FBO	Chemist	Others	Total
Nairobi	34.6	34.6	8.3	18.6	3.9	100
Central	69.1	18.0	10.5	2.3	0.0	100
Coast	56.3	27.0	2.6	12.5	1.6	100
Eastern	66.4	18.4	10.2	4.6	0.4	100
North Eastern	79.8	17.1	0.0	2.5	0.6	100
Nyanza	60.1	12.4	2.9	20.9	3.7	100
Rift Valley	55.4	20.4	8.7	12.3	3.2	100
Western	47.5	15.5	3.4	30.5	2.9	100
Cluster type						
Urban	45.5	29.0	4.8	18.7	2.0	100
Rural	59.5	16.8	6.8	14.3	2.7	100

Source: Kenya Health Expenditure and Utilization Survey Report, March 2009 USAID

About seventeen percent of rural residents visits private facilities for illness compared with 29 percent of urban residents (table 2). The column, Private in table2.2 includes private hospitals and private clinics. In Nairobi, the rate of these visits is twice as high (at about 35

percent) as in rural areas. Western and Nyanza provinces each at about 30 and 21 percent leads in utilizing chemist when ill. Almost 80 percent of outpatient visits in North Eastern is public facility

An analysis of utilization of inpatient health care services has shown a sharp increase from the admission rate of 15 per 1,000 in 2003 to 27 admissions per 1,000populations. Females are hospitalized more often (33 admissions per, 1000 population than males,19.8 per 1,000 populations). About half of the difference is attributable to childbirth and other reproductive health services.

Nationally, urban individuals have a higher admission rate (38 per 1,000 populations in 2007) than rural (24 admissions per 1,000 populations). This is attributable firstly, to greater access to health care and secondly, to the fact that urban residents can afford to pay for the health services.

There is also much provincial variation of hospitalization rates in Kenya. Nairobi and Central province reported the highest admission rate (34 admissions per 1,000 populations). North Eastern province had the lowest admission rate (7 per 1,000 population). A similar pattern existed in 2003.

Table 1.3:Inpatient Health Service by Income Quintile and Facility Type, 2007in percentage

Health facility type	poorest	second	middle	Fourth	Richest
Government hospitals	55.1	64.4	70.9	54.7	46.6
Private hospitals	7.2	4.3	7.5	21.3	29.1
FBO	14.7	16.9	12.0	14.2	13.0
Government health centres	13.2	9.2	4.0	3.7	0.6
Private health centres	2.8	1.8	0.7	0.6	0.2
Mission health centre	4.6	1.8	2.2	1.6	1.8
Nursing/maternity homes	1.7	0.0	0.9	2.7	7.8
All others	0.7	1.6	1.8	1.2	0.9
Total	100	100	100	100	100

Source: Kenya Household Health Expenditure and Utilization Survey Report, March 2009

Table 2.3 shows that the majority of in patients visit in 2007 were to public facilities. Even among the rich of population, nearly half (47) of inpatient care occurs at public facilities. Again, in all the wealth index quintiles, over 60 percent of all the inpatients in Kenya obtain their care at public hospitals. Notably, households at the top three wealth index quintiles utilize hospitals admissions than the lower two quintile. Nursing homes are relatively popular among the richest quintile.

This skewed utilization of hospital services is in favor of the households at the top of the wealth index. The distribution has three explanations. The first relates to physical location of hospitals. Since a large majority of hospitals are located in urban centres, geographical access to hospitals is much better for better-off urban dwellers than for poorer rural or slum residents.

Second reason relate to private cost associated with hospital use. Because hospitals provide more specialized treatments, the cost to an individual of using hospital services is much greater than that of using services supplied by health centres. This means that individuals with greater purchasing power have easier access to hospitals than the poor.

The third reason relates to the inequitable coverage of health insurance. As expected, individuals with health insurance coverage tend to be better-off than those without insurance coverage, because coverage is mandatory for persons with salaried jobs. Since health insurance agencies largely reimburse hospital costs, there is a bias toward greater use of hospital services by persons with health insurance cover.

1.6 Health Care Financing

Health care financing in Kenya is mainly through four mechanisms; taxation, development partner funding, NGOs finance, cost-sharing or system of user fees. The fourth source was initiated in 1st December 1989 after the government was faced with declining government revenue, an increasing demand for health services, and a continually growing population. The revenue generated from user fees and insurance claims are deposited into Facility Improvement Fund. This revenue is retained separately by the Ministry of Health, and is additional to budget allocations provided by Treasury. The revenue is used to improve the quality of health services in facilities and to support district-level preventive and primary health care services.

According to the National Health Account (Republic of 2009), the government contributions comprise 35% of the total health care expenditure. Government contribution to health sector has continued to increase in absolute terms, rising from Ksh. 15 billion in financial year 2002/2003 to Ksh. 32billion in financial year 2007/2008. However, as a share of government spending, the total health spending declined from8.3% of the budget in fiscal year 2002/2003 to 6.4% in fiscal year 2007/2008.

Ministerial Public Expenditure Review of 2008 shows that the per capita government expenditure on health has increased substantially in recent years, from US$6.1 in 2002/03 to US$13.8 in 2007/2008. The increase reflects the growth in absolute amount of expenditure allocated to health, which increased sharply between 2004/05and 2007/08. Despite this increase, the per capita health expenditure still falls short of the international benchmarks in terms of per capita spending, which was US$ 13.8 in 2007/08, compared with the WHO Commission on Macroeconomics and Health requirement of US$35 for MDG targets.

According to the NHA for 2009, households accounted for 29% of total health expenditure (Republic of Kenya, 2009). The households either pay contributions through medical schemes and other forms of health insurance or through out-of-pocket spending, popularly known asuser-fees. The households' contribution declined from 53% in fiscal year 2001/2002 to 29% in fiscal year 2006/2007. However, there are concerns that households still continue to be overburdened with heavy health care cost against a background of high level of poverty. This seems the case when one examines the contribution of user fees to the total funding for health facilities. The 2008 Public Expenditure Tracking Survey showed that user fees at district hospitals accounted for 67% of total funding. Similar patterns were reported for public government hospitals and rural health facilities.

The NHA reported that donors and international NGOs provided 20.8% of the total health financing in Kenya in fiscal year 2006/2007. It is imperative to note that around 90% of the donor funding to budget goes to the development budget. The NGOs mostly operate in rural and underserved areas, managing close to 18% of the health facilities in Kenya. They provide both curative and preventive services and rely on grants from donors and user fees. Their contribution in terms of financing the health sector has been minimal and was estimated at less than 1% in the fiscal year 2007/2008(Republic of Kenya, 2008).

The private sector represented by private-for-profit practitioners, private clinics and hospitals that specialize in curative services and offer preventive services to those who can afford, finances and manages about 29% of the total number of facilities in Kenya. This sector has developed over the past twenty years mainly as result of the decision by the Government in the late 1980s to allow clinical officers and nurses employed by the public sector to engage in private practice. The private sector accounts for about 4% of the total health sector financing.

The NHIF(National Hospital Insurance Fund) revenues have remained a significant portion of the total funding collected by hospitals since the mid-1990s (Republic of Kenya, 2009). The Public Expenditure Review of 2008 indicates that revenue collection by NHIF has been increasing over the years from Kshs.2.7 billion in fiscal year 2002/2003 to about Kshs.4.3 billion in 2006/2007. This growth is largely due to mechanism put in place by NHIF to enhance revenue collection, including enrollment of new members from the formal and informal sector.

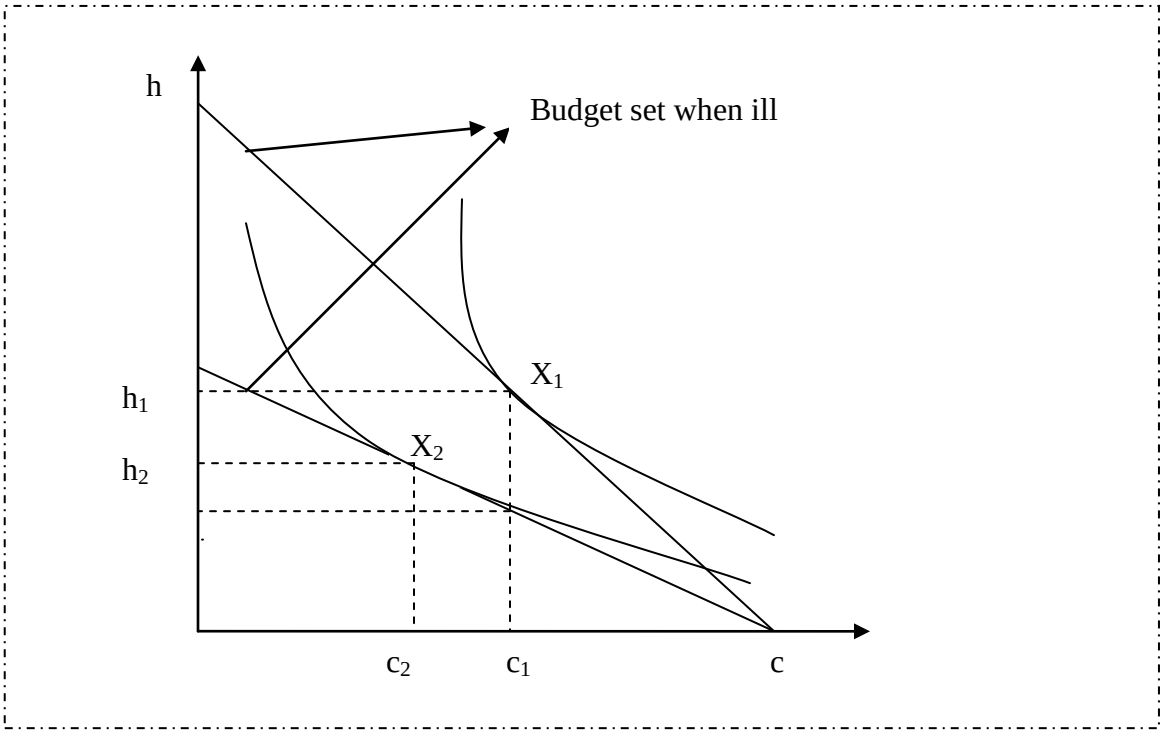
CHAPTER TWO: LITERATURE REVIEW

2.1 Theoretical literature

In the health economics literature, there are two alternative approaches to modeling decision making processes regarding health care utilization. One approach to modeling health care choices is to use an inter-temporal model of consumption decisions and treats health as a stock variable (Grossman,1972a). In this approach, health care is demanded in the context that it improves the stock of health and increases productivity. The second approach to modeling health care demand is to treat health care as one of the several commodities over which economic agents have well defined preference, (Phelps, 1992).

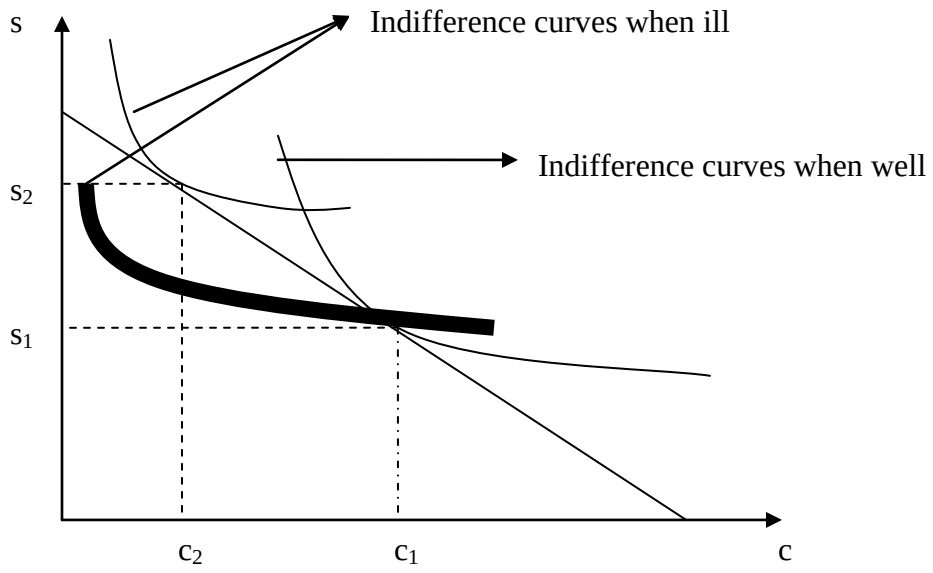
Following Grossman (1972b), the utility is defined as U(c,h), where c is considered consumption of other goods other than health care, and h is the level of health care. The theory assumes that utility is well defined, that is $U_c>0$, $U_h>0$, $U_{cc}<0$, and $U_{hh}<0$.Health care in this case is demanded only to the extent that it improves the underlying health of the individual, the effectiveness of which is determined by a host of factors, including the health itself. Using a utility maximization approach, Jack (1999) demonstrates that both price and health status affect the demand for health care (see figures 1a and 1b)

Figure 1(a) Equilibrium position when ill and well



Jack shows that if the price elasticity of demand for health lies between 0 and 1, the one-to-one relationship between {c, h}in Figure 1(a) space and {c,s}in Figure1(b) space can be represented through the above figures in which case s, in figure 1(b) represents health care. In Figure 1(a), (c_1, h_1) represents equilibrium pair when a person is well, while (c_2, h_2) represent new equilibrium when a person is ill.

Figure 1(b) indifference curve when ill and when well



The corresponding equilibrium pair of consumption and health care when well is represented as (c_1, s_1) in Figure1 (b). Similarly, the pair (c_2, s_2) in 1(b) corresponds to (c_2, h_2) in the consumption health space {c, h} showing equilibrium when ill. If the price of consumption is normalized to unity and the price elasticity of demand for health is between 0 and 1 then the pair{c_1, h_3}in {c, h} corresponds to an indifference curve that cuts the bold indifference curve at {c_1, s_1}. On the other hand, if the price elasticity of demand for health is greater than 1, then the indifference curve must cut the bold indifference curve from above in the {c, s} space. The implicit theoretical reasoning here is that, the effect of illness is to increase the price per unit of health. Jack has also demonstrated that the incidence of an illness might affect an individual's earnings thereby leading to potential income effects of illness and medical treatment.

In theory, the demand for health care is not only confined to quantities of health care, but most importantly to the choice of the provider. The theoretical orientation to the interaction of

quantities and health facility choice variables is extensively elaborated in the literature (see e.g. Mwabu, 1989b; Mwabu et.al, 1993; Sahn, 2003; Puig-Junoy, 1998; Castrol, 2002; Carol, 2007; Ellis et al 2004; Karen, 1991; Cameron et al, 1988; Feldestein,1995; Feldman et al, 1989; Luigi, 2006; Colle, 1978) . The existence of more than one provider means a somewhat different analytical framework is needed to estimate demand functions. Mwabu (1989a) and Sahn (2003) demonstrate that individuals are able to choose from a set of alternatives providers, where each provider-choice leads to a potential improvement in expected health for a given price. The price of an alternative may include both monetary (medical and non medical expenses, including loss of income) and non-monetary costs. Taking into account this information, the rational decision maker chooses the alternative that yields the highest expected utility. More precisely, the expected utility conditional on choosing an alternative, say j, can be written as $U(c_j, h_j)$, where c_j is the consumption net of costs of care by provider j and h_j is the expected improvement in health after receiving care from provider j.

Choice of medical treatment care facility is generally faced with information asymmetry. Once an individual falls sick he has to make a decision as to which health facility option to visit for treatment. It is assumed in the initial stage, that the person has no information about the quality of the facility to visit. Following Akerlof (1970) it is appropriate to assume that, there are good and bad quality health facilities, but the patient cannot tell them apart before making a visit. The patient has to resolve this information uncertainty about prior to visit. Arrow (1963) theoretically suggests that patients prefer organizations that are not maximizing profits when they are unable to judge quality directly, fearing that the profit motive might have adverse health consequences. He argues that non-profit hospitals serve a special role in helping patients judge quality in the health care market characterized information asymmetry. Several studies have shown how information is diffused to the consumers (Carmichael,1977, Shampine,1998; Kapur,1995; Abrahamson, 1997; Oriana,2006)

Leonard (2002) and Leonard et al (2005), present an elaborate framework of how information asymmetry could be reduced through outcome contingent contracts. The crux of this framework is that the patient pays for treatment only after being cured. In this type of payment arrangement, it is argued that the patient can observe the effort of the practitioner, which ultimately signals the providers' quality, thus resolving the information uncertainty about making visits to this specific health provider. This payment arrangement is common with traditional

healers in Africa, who require a small down payment before commencing provision of the health care, with the balance being paid once cured (Leonard, 2003). The argument is that, the patient fears that, in case of a deliberate default in payment, a curse is likely to befall him or his close relatives or is likely to be harmed by the healer. Thus there is no need for a formal legal system to enforce contracts in this type of healthcare market. In practice however, this form of payment mechanism is impossible to enforce the formal health care markets because the belief systems of patient in these markets are different from those prevalent in traditional healers health markets.

2.2 Review of Some Studies done on Demand for Health Care

There is a vast and growing literature on developing countries analyzing health care demand decisions of individuals faced with an illness or injury. Examples of empirical studies in the recent past include Glick, et al (2000), Sahn, et al. (2003), Deininger and Mpuga (2005), and Lindelow (2005). These studies hinge on the concept of utility maximization when preference are defined consumption of health and non-health goods, and focus on three health care decisions. First, the decision on whether or not an individual reports illness or an injury. Second, the decision on whether or not to seek formal health care when ill. Third, the choice of health care provider once the decision to seek care is made. This is what Mwabu (1984; 1986) referred to as the multi-stage decision making process in health care. In the three decisions, the emphasis is mainly on an individual who reports an illness or an injury during a specific recall period. Focusing only on an individual who reports illness, however, points to a selection bias (Akin et al., 1998; Dow, 1995). This is because an assumption is made that people who do not report illness do not demand health services. Alternatively, reporting of illness could be due to an individual's sensitivity to health rather than to illness itself within the health status space.

In the empirical literature, a variety of empirical specifications have used discrete models to estimate parameters of these demand models. The models specification include the multinomial logit, Mbanefoh and Soyibo(1994) in Nigeria;, multinomial probit, such as Akin et al. 1995 in Nigeria; mixed multinomial logit such as Mwabu et al, (1993); in Kenya, Lindelow (2005) in Mozambique and nested logit(Sahn et al, 2003) in Tanzania. The multinomial logit model however suffers from the independent of irrelevant alternatives (IIA) restriction. The IIA property assumes that all alternative subgroups are not correlated at all, and the cross price elasticities are constant across subgroups, and as such leads to biased estimates, because the

subgroup correlations are ignored during estimation. Subsequent studies have employed alternative model specifications that are not restricted by the IIA property (see Bolduc et al, 1996; Dow,1995). These models include the multinomial probit and nested multinomial logit. The Multinomial probit remains unpopular due to the difficulties involved in its estimation, but this problem has been mitigated by recent advances in computational algorithms (see Dow, 1995).

At the level of health care provider, the quality of medical care in terms of technical efficiency as proxied by availability of drugs has been cited as a key determinant of demand for health care (Sahn et al., 2003; Mwabu et al., 1993; Ellis et al, 1994). A common source of market failure in the health care market is that individuals do not have full information concerning health benefit of treating illness at alternative facilities. This inadequacy may cause patients to neglect appropriate preventive actions (Hsiech and Lin, 1997). Lack of adequate health information has been associated with variations in health care utilization at various health facilities, and especially between rural and urban sector as noted by Thompson (2003) when using Kazakhan data in analyzing health-seeking behavior of rural and urban households. There are studies that have analyzed the role of information on the demand for medical care (Kenkel, 1990; Hsiech and Lin, 1997). Using probit results, Kenkel (1990) indicated that more informed consumers are likely to visit a physician. This is consistent with the argument that poorly informed patients tend to underestimate the marginal product of medical care ,but there is need to note that they can overstate it. This hypothesis is further supported by findings of Hsiech and Lin (1997) amongst the elderly in Taiwan. They found that, better informed elderly people are more likely to use preventive care. However, these results should be interpreted with caution since they are likely to suffer from selection bias, since only one age category was analyzed.

Some studies found that prices are not important determinants of medical care(Akin et al.,1985; Akin et al, 1986; Schwartz et al, 1988; Birdshall and Chuhan, 1986; Heller 1982; Christian, 2003), while other studies found that prices are indeed important determinants of demand for medical care(Mwabu,1986; Mwabu et al.,1993; Dor et al.,1982; Gertler et al 1987; Gertler and van der Gaag,1990; Bolduc et al.,1996; Dow, 1995; Dow, 1999; Deborah,1989). All these studies employ discrete choice models to analyze the choice of health care provider. However, the methods and results on the price and income elasticities are confounding across

studies thereby making general policy implications difficult to generalize and sometimes even inconsistent (see Gertler van der Gaag, 1990; Jimenez, 1995; and Gertler and Hammer, 1997 Janet et al,1994; Krisha,2006). Many of the studies contradict the findings from the developed countries where price elasticities range from -0.2 to -2.1(Mwabu, 2008). These conflicting findings may seem to be paradoxical because one might expect price elasticities to be higher in developing countries due to low income and high uninsured population (Gertler and van der Gaag, 1990). On the contrary, price elasticities may not be higher because price per unit of care is much lower in developing countries, indicating that health care consumers are at the low end of the demand curve. Moreover, the health seeking behavior of the people in developing countries might not correspond to that of the behavior patterns of developed countries.

Sahn et al. (2003) found that the responsiveness of price to be greater for individuals at lower end of the income while own price elasticities are high, although less for public clinics and dispensaries than other options. It is evident in the literature that when prices of health care services are increased there will be a precipitous decline in use of those services. This proposition is strongly supported by studies that have analyzed the effect of user fees on medical care demand such as(Mwabu et al, 1995) in Kenya, (Waddington and Enyimayew, 1990) in Ghana, (Yoder, 1989) in Swaziland, (Kahenya and Lake, 1994) in Zambia and (Sahn et al., 2003) in Tanzania. These studies have reported declines in the use of public clinics subsequent to the imposition of user fees. The Tanzanian case was surprising in that user fees resulted in a high degree of substitutability between public and private clinics. This meant that user fees were not likely to force a big percentage of people changing to self-treatment (Sahn, 2003). This kind of a result indicates that government should adopt a policy of improving the quality of health care, rather than suspending the user fees. Such a policy would contradict Segall (2000) andThompson (2003) who indicated that lack of free access to health care for the poor in Vietnam turned them to self-medication, as a first-line strategy for dealing with illness.

Gender issues in the access to health services have been incorporated in a number of studies, for example; (Mwabu et al., 1993) in Kenya ; (Sahn et al., 2003) in Tanzania; (Hutchinson, 1999) in Uganda; and (Wong et al., 1987) in Philippines. Mwabu et al, (1993) found that distance and user fees were both factors that reduced demand for health care, but men were less constrained than women. Increase in woman's earning in a household resulted in a decrease in the use of modern curative services, reflecting a greater value for her work than time

spent seeking care (Hutchison, 1999). Substantial gender bias was present in Sahn et al., (2003) in that men were less likely to seek out available treatments at public clinics and dispensaries.

Hutchison (1999) found that individuals in households with women of higher levels of education were more likely to use curative care. Still, on education and gender, Jaurez (2002) and Wong et al (1987) found that for both rural and urban mothers, the likelihood of choosing public clinic as the most frequently used option increases as education level increases. An emerging pattern in health service utilization is that the time constraints and opportunity costs faced by women are higher than for men, thus deterring them from accessing health services to a much larger extent.

Cisse (2006), in an analysis of health care utilization in Cote d'Ivoire found that household headship, education level, drug prices, and income and distance to be positively related to health care utilization. Conversely, higher drug prices and long distances to provider decrease the probability of using formal medical care. The effect of household size on the demand for healthcare has been found to be positive and significant (Sarma, 2003; Hallman,1999), though Sahn et al. (2003) observed that large households sought care from non-hospital facilities

2.3 Synthesis of the literature

Past studies that have examined health information have looked at health status through its impact on demand for medical services (Kenkel, 1990; Hsiech and Lin, 1997). But these studies did not attempt to assess how patients gather information on the quality of the health provider given that he or she is faced with information asymmetry as to the quality of care offered. Information about health care is crucial because it is needed in the second stage of multi-stage decision making discussed earlier. That is, it is needed in determining which health facility to visit once a patient has formed a decision to seek medical attention. This study sheds light on this very important area of research.

Many studies have looked into the determinant of quality of care using varied definitions of quality. In theory, quality of medical care can be assessed through three distinct ways. First, we have the process indicator of quality. Process in medical care details the way patients are handled when they seek for medical care. For instance are the health personnel friendly? The second indicator of quality is the technical efficiency. Technical efficiency entails availability of

drugs and medical hospital equipment and supplies. The third indicator of quality is the outcome of treatment. Outcome of treatment is the ultimate result of medical care, which is manifested by the health status of the patient after receiving medical treatment. This study further examines the interaction between technical efficiency and the process indicators of quality in an explanatory model of the demand for medical health care.

CHAPTER THREE:ANALYTICAL FRAMEWORK

3.1A model of medical care demand

Health care is a consumption good as well as an investment good. Health care consumption improves health which in turn increases utility. To this extent, health care is a derived demand. As a consumption good, health care improves welfare, while as an investment commodity, health care enhances the quality of health human capital by improving productivity and increasing the number of days available for productive activities. Time lost in production because of ill health reduces output in market and non-market settings

Following Grossman's (1972) model, individuals maximize their utility subject to a budget constraint. Health is a component of each person's utility function; however, as Grossman noted, health cannot be directly purchased. Rather, an individual has a durable"Capital" stock that produces healthy time. An individual's initial stock of health depends partly on genetics. The health stock then decreases through the normal course of aging, until death. One can slow health decrements by consuming medical care and by pursuing healthy behaviors, both of which are considered inputs in the production of health.

Following Appleton (2000), some insight into the effects of health status on health care demand can be provided by looking at health status (H) as something produced by the household. For instance, if one considers the health inputs, S, which are demanded at least partly in order to generate productive health status, a simplified utility maximizing model of a single household can be stated as

$$U = U(H, L, S, Z) \quad \text{---------- (1)}$$

Where, L, is leisure and Z consumption of all other goods that do not contribute to health status. H and S enter directly into the utility function as they may be intrinsically desirable, e.g. given H, S could be inputs into health production including nutrients and medical treatments. The utility in equation (1)is maximized subject to three constraints:

The first constraint relates to a health status production function, which could be a health production function (Grossman, 1972). This is a technological relationship, reflecting purely biological processes, but the inputs are, to a certain extent, choice variables. This health human capital production function can be denoted as:

H = H (S, T; Q, d, L, m)---------- (2)

where:

S= Quantity of health services used as inputs into health production

T= household time devoted to health status accumulation(on health or medical care)

Q= the quality of the services S provided.

d= observable household characteristics

L= relevant community- level characteristics

m= unobservable household characteristics

If we take T to be medical consumption, then its demand is derived from the need to improve health status which is a derived demand.

Other constraints include a wage function:

W = W(H; d, I, a) ---------- (3)

where:

I = relevant community characteristics (e.g, local infrastructure that affects demand for labour)

a= unobservable household characteristics such as ability

There is also an income constraint in health production: in producing health, the household can spend no more on goods and health inputs than their total resource endowment

Z + Ps.S = W.L + V ---------- (4)

where

V is unearned income

P_s are prices of services (where the price of Z is normalized to 1)

Finally, there is a time constraint with a fixed endowment of time, normalized at 1, being allocated to wage labor, health status acquisition and leisure, R.

$1 = L + T + R$----------(5)

Maximizing (1) subject to (2), (3) and (4), and holding consumption of other goods constant yields reduced form demand function for health care of the form:

$S = S (H\ Ps, P_h\ V, d, I,$ □,-,□)----------(6)

Equation (6) shows that health status affects the demand for health care services.

3.2 Specifying conditional demand for health care.

Demand for health care is established by assessing the decision of the household during an episode of illness. When one gets ill he can decide either to seek for medical care or not to seek for medical care but not both.

Among the many factors that determine the choice of the facility to be visited, is the quality of the health facility. As already noted, quality will includes process, technical efficiency and outcome factors. Good quality attracts patients to a facility, cetris paribus.

For each health facility that can be visited, there is a utility that a person derives from choosing it.

For each alternative health facility j, the individual's utility at time t is given by conditional utility function of the form

$U_{ij} = U(H_{ij}, C_{ij})$---------- (7)

Where H_{ij} is the expected health status of individual I at health facility j at time t and C_{ij} is the consumption of goods other than health on visiting a health facility. Further, H_{ij} and C_{ij} are re-defined as

$H_{ij} = h[(Q_{ij}, X_i, Z_j), H_{i0})]$ ---------- (8)

where

Q_{ij} is health care index quality at provider j as perceived by the ith individual , X_i represents individual patient characteristics at time t;, Z_j is a vector of provider characteristics at time t; and H_{i0} is the initial health status of patient i.

$$C_{ij}= Y_i- P_j \text{ ---------- (9)}$$

Where,

$Y_i$is the individual income at the current time period and P_j is the price charged by provider j. where the quantity bought is normalized to unity

The budget constraint is defined as

$$Y_i = C_{ij} + T_{pij} \text{ ----------(10)}$$

Where

Y_i=total income of patient i

T_{pij} is the total price of patient i choosing provider j

Assuming away price discrimination, the total price can be divided into two that is, the monetary price and the time price. Monetary price is the price paid in money terms while time price is the opportunity cost of time devoted to traveling to and waiting at health facility.

Thus the overall budget constraint is

$$Y_i = C_{ij} + M_{ij} + N_{ij} \text{ ---------- (11)}$$

Where,

M_{ij} represents the monetary price of the provider j and N_{ij} is the nom-monetary price.

N_{ij} can further be expressed in terms of the travel time and waiting time associated with the choice of alternative j.

$$N_{ij} = c_i \bullet (T_{ij} + W_{ij}) \text{ ---------- (12)}$$

Where,

c_i is the opportunity cost of time for individual i for the non-monetary price, T_{ij} is the travel time while W_{ij} is the waiting time, all associated with the choice of alternative j.

Substituting for H_{ij} and C_{ij} in Equation (8) , the conditional probability may now be expressed as

$$U_{ij} = U(E_{ij} + H_{i0}), Y_{i-} P_j - w_i T_{ij} - w_i W_{ij} \text{ ----------} (13)$$

Where E_{ij} is expected level of health that patients I expects after seeking treatment at provider j

Further, the probability that patient i choose alternative j depends on the observed attributes of alternative j and the observed characteristics of the decision maker.

From equation (13) the conditional probability of visiting a particular health facility can be derived as in Gertler and Vander Gaag(1990)

3.3 Information asymmetry and medical care demand

One of the implicit assumptions of the fundamental welfare theorem is that the characteristics of all goods and services are observable to all the market participants. Without this condition, distinct markets cannot exist for goods and services having differing characteristics, and so the complete markets assumption cannot hold. In reality however, this kind of information is often asymmetrically held by market participants. A great in sight into this phenomenon was provided by Akerlof (1970) in the context of the market for “lemons”, where the term lemon was used to mean a used car.

In case of the health care market, the health provider may have better information about the quality of health services provided by his facility than that a member of a household can have. In this case, the quality of the health facility is unobservable by the household, and this leads to information asymmetry in health care markets. Thus, the information patients possess about the quality of available health care facilities affects health care demand, and thus information should be taken into account when estimating health care demand models.

3.4 Discrete choice health care demand models

Following Gertler and Vander Gaag (1990), the conditional probability for a particular health facility can be expressed as

$$P_j = e^{vj/\sigma} / \sum e^{vj/\sigma} \text{----------(14)}$$

Where P_j is the probability of facility j being chosen

Vj = expected utility conditional on treatment at facility

$^{\sigma}$ = dissimilarity parameter that determines the nature of the model to be estimated.

3.4.1 ConditionalLogit

From equation (14) several discrete choice models of health care demand can be derived including conditional multinomial logit model, nested multinomial condtional logit model, flexible multinomial logit model, and multinomial probit model(see Green,1997; McFaddan,1981; Koppelman et al, 2006) . These models are distinguished by the functional form for utility function V_j and the distributional assumptions made about the disturbance term for v.

If in equation (14), the dissimilarity parameter is equal to unity, then the estimatable discrete choice model of health care demand belongs to the family of the multinomial logit models. The earliest and most famous of these is the conditional logit model(see McFadden 1974).

In this model, the probability that a patient will choose a particular facility is expressed as

$$P_j = e^{vij} / \sum e^{vij}$$

Where

$$V_{ij} = \alpha W + e_{ij} \text{---------- (14a)}$$

Where, W is an attribute of health facility such as price. In this specification, only one coefficient for the facility is estimated irrespective of the number of alternative health facilities available. For example, if W represents distance to five health facilities, only one coefficient for distance is estimated. The idea here is that the marginal disutility of one unit of distance to any

health facility is the same and constant. However, this specification suffers from the IIA assumption that can bias the estimated coefficient.

If in equation (14) the value of dissimilarity parameter lies within the unit interval, the estimatable model of health care demand is the nested conditional logit model. Elaborating equation (14), the probability of a visit to health facility can be specified as in(see Sahn et al, 2003). The expression for the probability that an individual chooses option c is given by

$$\pi_h = \frac{\left[\exp\left(\frac{V_h}{\sigma_j(h)}\right)\right]\left[\sum_{i\in j(h)}\exp\left(\frac{V_i}{\sigma_j(h)}\right)\right]^{\left(\sigma_{j(h)}/\tau_{k(h)}-1\right)}\left[\sum_{j\in k(h)}\left[\sum_{i\in j(h)}\exp\left(\frac{V_i}{\sigma_j(h)}\right)\right]^{\left(\sigma_{j(h)}/\tau_{k(h)}\right)}\right]^{\left(\tau_{k(h)}-1\right)}}{\sum_k\left(\sum_{j\in k}\left[\sum_{i\in j}\exp\left(\frac{V_i}{\sigma_j}\right)\right]^{\sigma_j/\tau_k}\right)^{\tau_k}}$$

Source: Sahn et al. 2003

Where,i represents the individual options(public hospital, etc.),j represents the lower level nest. V_i is the indirect utility associated with option i, σ_j is the inclusive value coefficient for the lower nest, τ_k is the inclusive value coefficient for the upper level nest and $_j(h)$ and $_k(h)$ indicate the lower and upper level nests to which option h belongs.

Conditional on choice of facility, the intensity of service use will be studied.

The above expression indicates that nesting the logit choices allows us to estimate at least some of the covariances between the e_j's, which in turn allows cross-price elasticities to vary between options.

Under this specification, the coefficient on W in equation (14a) can be made constant or be allowed to vary across health care facilities. The nested logit model resolves the estimation bias due to IIA, but the additional assumption that marginal utility of income is constant across health facility could be strong. Dow(1995, 1998) has convincingly argued in favor of relaxing this assumption, to obtain what he call the flexible multinomial logit model of health care, and has the form

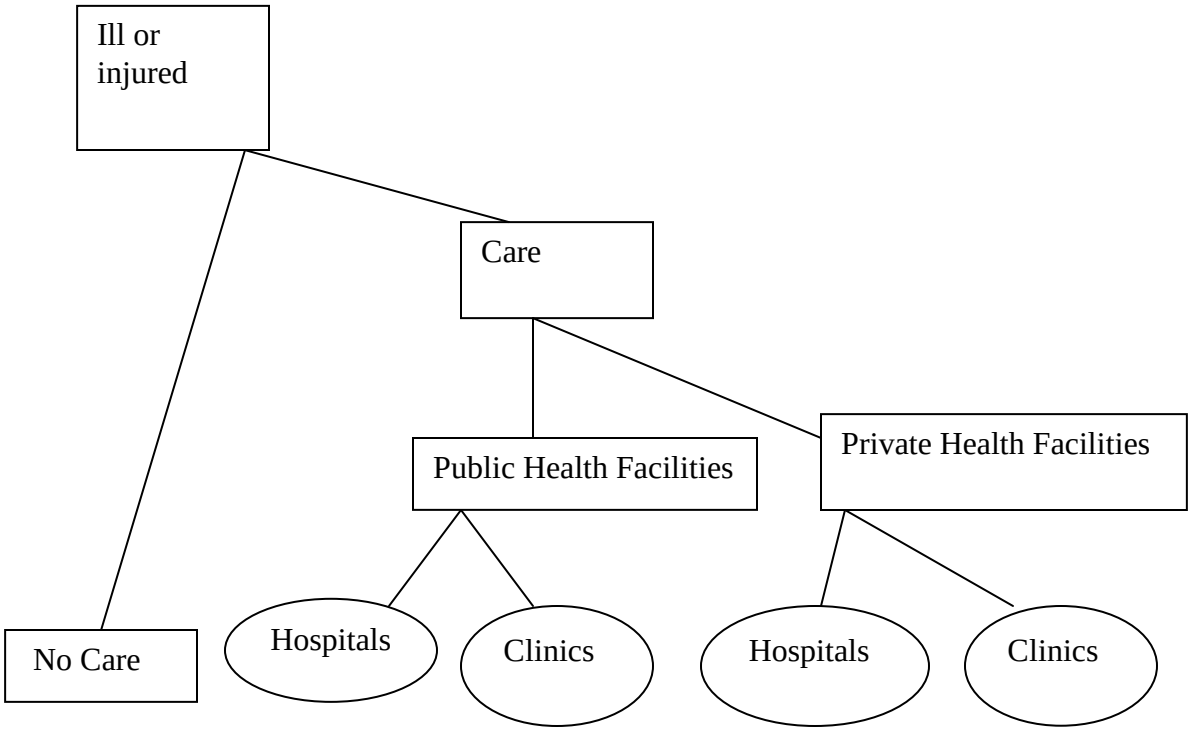
$P_{ij} = e^{Vij}/\sum e^{Vk}$

Where

$V_{ij} = \beta_j W_j + e_{ij}$ ----------(14b)

Where the coefficient on W now varies with health care provider. However, the flexible MLM suffers from the IIAassumption. Buldoc et al and Dow(1999) show that multinomial probit model relaxes this assumption and is more general than the nested logit model.

Figure 2:The EstimatedTree structure of health facilities



Conditional logit specification assumes that the choice alternatives are independent from each other in that the error terms in each option are unrelated, but the error for utilities in the same nest are correlated. The difference between conditional logit and multinomial logit is that in the conditional logit model,the estimated coefficients ongeneric regressors do not vary by alternatives.

Our conditional logit model is expressed as

The prob $(y = j) = e^{\beta vij} \Big/ \sum_{j=1}^{j}(e^{\beta vij})$ ----------(15)

Where

y is a random variable which indicates the choice made

v_{ij} includes characteristics of the individuals as well as of the choice alternatives, so that

$V_{ij} = [X_{ij}, Z_{ij}]$----------(16)

Since $\exp(\beta v_{ij})>0$ these probabilities lie between 0 and one andsum over to j. Given that probability y =1, an equivalent model is obtained by defining v_{ij} to be deviation of regressors from values of say alternative1, and setting $v_{ij} = 0$

In our current specification Xs are the individual attributes like sex, age, education, occupation, trust, assets, information and household size. Zs on the other hand are the facility specific attributes, like quality, distance, waiting time, user fees, and information on quality at different facilities.

3.4.2 The Multinomial Logit Model

In multinomial logit model an individual is assumed to know all the provider-specific attributes and to choose the alternative that maximizes his utility. The observed choice is determined by the differences in utility across alternative, rather in than levels of utility. This implies that the visit decision will involves a comparison of theutility obtained from each option. AMNL model is specified as:

$(y_i = j) = e^{\beta jVi} \Big/ \sum_{j=1}^{j}(e^{\beta jVi})$ j= 1…..,j---------- (17)

because $\sum_{j=1}^{J} y_i=1$, a restriction is needed to ensure model identification and the usual restriction is that $\beta_1=0$. While in a conditional logit values of Xs are used as deviations from their means in a multinomial logit deviations in coefficients are used to compute marginal benefits expected at alternative source of treatment. The facility with the highest benefit is chosen;

$V_{ij} = pr(V_{ij>} V_{ik})$ for all j≠k ----------(18)

Where V_{ij} is the probability of visit to facility j by individual i while V_{ik} is the probability of visit to facility k by the same individual i ,Vij are expected benefit of treatment that individual i expect at facility j.

In the case where some regressors vary across alternative e.g. distance to clinics and other regressors do not vary, e.g. gender of the decision maker, the two models are combined to yield a mixed logit model which is a special case of the McFaddens conditional logit model(see Cameron and Traved 1986; Dow, 2004).

As previously noted, the multinomial logit has the restrictive assumption of the independence of irrelevant alternatives (IIA). The IIA as seen earlier imposes the equal response elasticities across choices. This means that the introduction of additional choice decrease the predicted proportion of the sample that chooses each of the original alternatives in proportion to their size before the introduction (Hoffman and Duncan 1988).This is a very strong assumption. It states that there are no sub-group within the alternatives that are closely related. Rather, all facilities are independent in such a way that any introduction of an extra option will reduce visit probabilities equally across alternatives. However, intuition will dedicates that government facilities, i.e., public clinic and public hospitals are more likely to be related in one way or the other in terms of their un-observables such as the quality of medical personnel. Inevitably, the same case should apply to private clinics and private hospitals. In essence, introduction of an alternative facility like, a community health care center in the sub-group of government facilities will be expected to reduce the probability of visits in that sub-group but not in the sub- group of private facilities.

The attractiveness of MNL is that, it is simple to estimate, and interpret the estimated parameters. Its drawback is the IIA assumption.

3.4.3 The Nested Multinomial Logit model

This model is a generalization of the basic multinomial logit (Henser, 1986). It is the ideal one to use when there is a clear nesting structure, but not all multinomial choice applications have an obvious nesting structure. The nested multinomial logit specification,

allows correlation of sub-groups of alternative and not the base option of no-care/self-treatment. This is unlike MNL which suffers from IIA assumptions. The nested logit groups similar choices and selectively relaxes the IIA. A good reason for using nested logit is that it allows one to test the appropriateness of correlation between options using the inclusive value parameter. An inclusive value parameter that has a value to one or above impliesa case of independence of the disturbance term, thus begging for either conditional logit or multinomial logit estimation. For a mathematical treatment on this issue see McFadden, (1978); and Cameron and Traved,(1986) Horowitz, (1987) Koppleman, (2006).

3.4.4 Multinomial Probit Model

An alternative and obvious way to introduce correlation across choices in the unobserved component is to work with models with normally distributed errors.

The multinomial probit specification provides the general framework to study discrete choice models since it allows correlation between all alternatives. This specification is the result of the assumption that the error terms are identically normally distributed. Multinomial probits are less restrictive than multinomial logits and even less restrictive than nested logits because they completely relax the IIA assumption.

The multinomial probit specification results if we assume that the e_{ij} are identically normally distributed with covariance matrixΩ. The probability of observing an individual choosing alternative k is given by:

$$P_{ik} = \int_{-\infty}^{A_1} \int_{-\infty}^{A_2} \dots \int_{-\infty}^{A_{k-1}} \psi(\mathcal{U}; \Sigma)\, \partial\mathcal{U} \quad \text{---------- (20)}$$

Where $A_j = (\overline{Z_{ij}} - \overline{Z_{ik}})\beta + X_i(\overline{\gamma_j} - \bar{\gamma}_k)$, $\mathcal{U}$ is a (K X1) zero mean vector, $\psi(.)$ is a multivariate normal density function and $\sum$is the covariance matrix of the different error terms.

The main impediment to the use of this specification is the dimensionality of the response probabilities. Recent solutions to the dimensionality problem have been proposed by MacFaden(1989) and Pakes and Pollard(1989).

The random utility model associated with a visit to a health provider under the above specification is

$V_{ij} = V(X_i, Z_j, I_i) + e_j$ ----------(21)

Where,

Xs are individual specific variables like sex, age, occupation, education, assets, household size, and trust; Zs are the facility attributes like distance, quality and user fee while I is the information index that individual i associated with health facilities.

CHAPTER FOUR:STUDY AREA, DATA METHODS AND SAMPLE STATISTICS

4.1 Introduction

This chapter describes the study area, sampling procedures, methodology of data collection and presents descriptive statistics.

4.2 The Kibera informal settlement

Kibera lies at an altitude of 1670 meters above sea level and 140km South of the equator. Kibera slum is the largest informal settlement zone in Kenya. It is approximately seven kilometers from the Nairobi city centre.

Kibera started as a privileged settlement for ex-African soldiers (mainly of Nubian and Boran origin) who served under the British Army during the first and the second World wars. At independence, most of the former soldiers were assimilated and naturalized as Kenyan citizens. They became the first landlords of Kibera as Nairobi continued to grow. Due to acceleration of rural-urban migration in search of better-paying jobs and improved livelihoods, increasing pressure for low-cost housing in the city made Kibera settlement an automatic target for development of informal temporary structures. As this trend continued over the years, Kibera has grown to become one of the largest slums in East and Central Africa, housing more than a quarter of the Nairobi population. Kibera as a whole is an informal settlement, comprising nine villages covering approximately 223.4 hectares of land, with an estimated population of about 700,000 people.

The average population density is over 2000 people per hectare although some villages are more crowded than others. The Kibera villages are Lindi, Kisumu Ndogo, Soweto, Makina, Mashimoni, Silang, Laini Saba, and Gatuikira. The average home size is $9m^2$ with an average household size of five. The living conditions in Kibera are representative of the state of urban poverty. High population densities, poor sanitation and poor water quality, low access to basic

services like health care and education. Further, Kibera residents lack legal rights like security of tenure, leaving them without power to ask structure owners to provide housing maintenance or basic services.

Urban interventions that address the issue of slums have been triggered only by external factors such as land development and speculation, health and safety concerns, and threats to the wealth owned by external landlords.

Compounded by lack of a clear framework, there are no effective government programs for meeting the needs of the residents of Kibera informal settlements. Poor water supply and sanitation are the most serious infrastructural problems in the area. Notable interventions have only been received from external agencies, such as donors and NGO's. However these efforts are still to a large extent uncoordinated.

The quality of housing in Kibera is very low. The houses are constructed of temporary or semi-permanent materials and are built without due consideration to structural requirements. This is mainly because most of the slum dwellers are squatters and therefore cannot build permanent structures since they do not enjoy the security of land tenure. They live on land on which they do not have legal rights to ownership. Their structures are very often demolished by the city authorities without notice or compensation for damage or loss of property. As a result, the Kibera slum dwellers have low incentive to invest in permanent housing structures.

In Kibera, the mode of land occupancy is predominantly squatting on private or public land without permission by the owner. They have some quasi-legal tenure through letters of allotment from the local chiefs or some form of agreements with the landowners on private land. Another mode of land occupancy in Kibera involves temporary occupancy licences by the city council. In this mode of land occupancy, the allottee is given permission to use vacant land on temporary basis.

Various non-governmental organizations have sponsored slum upgrading projects over the past several decades with varying degrees of success. Acknowledging the problem's severity and persistence, Kenya's government took definitive action in 2002 by creating the Kenya Slum Upgrading Program (KENSUP). KENSUP focuses on implementing projects that are sustainable, inclusive, democratic, accountable, and transparent and that will provide slum communities with improved housing and access to basic services, secure tenure, and

opportunities to generate income. KENSUP's project in Kibera's Soweto village is one of the pilot projects. It is a joint effort between the Kenyan government and UN-HABITAT.

4.2.1 Economic Characteristics

Kibera informal settlement is characterized by poverty and poor housing. The distribution of income within Kibera slum is very heterogeneous. The distribution has three strata:a category that depends on business and slum lordship; a category that relies on wage employment; and a category that relies on unpredictable and unsteady income sources. The average income for household in the slum is around kshs 8,500 per month while the average income per capita is Kshs 1420 per month (GOK and UN-HABITAT, 2005).

4.2.2 Health and the Environment

Health related issues

The poor environmental living conditions and the inadequate food intake in the slum combine to increase the incidence of poor health among the households. Households in Kibera spend less on health, clothing, and education and on leisure. Households spend a small fraction of their income on health not because health problems are absent in Kibera but because they cannot afford the cost of health care.

Malaria is the leading health problem in Kibera. The poor drainage systems in Kibera slums are conducive to mosquito breeding and other disease vectors. The second leading health problem in Kibera is HIV/AIDS. Like malaria, it is one of the leading killer diseases in Africa. In Kenya, over 2.2 million people are living with the virus, with 1/5 of this figure living in Kibera (GOK and UN-Habitat, 2005). It is estimated that 10-25% of Kibera's resident are infected with HIV (UNDP 2005), a rate more than double the national average. Due to poor drainage, coupled with lack of hygienic disposal of human waste and lack of adequate supply of safe drinking water, diarrhea and typhoid are rampant in Kibera.

Health provision in the slum is through a network of public, private and NGO health facilities. The NGO's health facilities, consisting mainly of clinics and dispensaries, are the most common in the slum. There are occasional mobile health clinics operated by the government. The major health facilities that are nearest to the slum are Woodley Clinic, Kenyatta National

Hospital, Mbagathi District Hospital and the Prisons Clinic along Langata Road. The slum residents also live within the proximity of Masaba hospital, Coptic hospital, St. Mary's hospital and even Nairobi hospital, but cost of care in these health facilities are prohibitive.

Environmental issues

In Kibera just like other informal settlements in the city, the Nairobi City Council (NCC) waste collection services do not exist. Due to lack of water, sanitation and hygiene, prevalence of diseases is common. The NCC does not recognize existence of the informal settlements and therefore does not provide waste management services on their own. Unlike the middle and high-income residents in Nairobi, the informal settlement residents are too poor to afford private waste collection services. In 2000, AMREF initiated a community based refuse collection bins for Kibera residents. The residents did not use the waste bins for waste collection and storage purposes but instead, the containers were used for fetching and storage of water, washing clothes and bodies (Karingi, 2004). The project collapsed and leaving communities without organized waste collection services.

Poor sanitation is a key problem in Kibera**.** Latrines in Kibera are in great shortage, a situation brought about by the tendency of landlords to construct income-generating housing units instead of economically unproductive toilets. Pit latrines are the primary sanitary facilities with about 70% of the households having neither a formal nor an informal connection to a sewer, and relying on pit latrines that are not always emptied when full. Most pit latrines are shallow and poorly constructed with no vents and offer little privacy to users. Households use the latrines for bathing, washing and in most instances, disposing solid wastes. Residents pay an estimated fee of Kshs 100 per month for the use of communal or plot-based latrines. In spite of the increasing population, Kibera has continued to lack adequate toilet facilities, resulting in up to 150 people sharing one pit latrine in some places. Between 50-90% of the households do not have access to adequate sanitation due to lack of adequate space to construct new facilities and the failure to empty pit latrines that get full. About 68% of households rely on shared facilities with a high loading factor. Toilets in areas of high water table flood, and overflow into drainage trenches during rainy seasons and eventually into the Nairobi Dam. The lack of space in-between the housing units in Kibera deny NCC access to filled toilets causing a serious sanitation problem. Insufficient availability of latrines has led to alternative methods of human waste

disposal such as the use of “flying toilets” (waste tossed up in wrappings) and open place toilet. Women and children, due to insecurity and fear of mugging, cannot access latrines at night. In Kibera, most households lack proper bathrooms as only 46% of the residents have access to a bathroom (USAID, 1991).

A rapid need assessment study carried out in 1997 for the preparation of the Kibera Water Distribution Infilling Component (KWDIC) described the water supply situation in Kibera as inadequate, irregular and quite limited. Despite improvement in Nairobi’s water supply, including the commissioning of the Ndaka-ini Dam in 1996, the water supply situation in Kibera has not changed. Within Kibera, the quality of water is poor as water is contaminated by infiltration of liquid waste into burst pipes. There is always high a risk of waterborne diseases within the community. Although Kibera holds more than a quarter of Nairobi’s population, the consumption of water by the residents of Kibera is a small fraction of the city’s water supply (less than 10%). Kibera receives an estimated 200,000 m^3 of water per day, 40% of which is lost through leakages. There are approximately 25 kilometers of piped water network in the entire settlement, but much of this network receives little or no water.

Access to water is mainly through water vendors or water kiosks operated by individuals or NGOs. The average distance to the nearest water kiosk is about 40 meters and consumption ranges from 16 to 20 litres per capita per day with an average daily water consumption by a household being approximately 60 Litres. Characteristically, water kiosks sell water at three to four times the tariff charged by the Nairobi water supply company. The vendors charge inflated rates of between Ksh 10 and 20 for a 20-litre jerry can, while those operating community water points charge Ksh 2-5 for the same amount of water.

4.3 TheSample and the sampling technique

4.3.1 Target population

The target population consisted of the resident of Kibera slum. The survey covered people who were currently staying in Kibera at the time of the study. In this particular case, the survey was restricted to residents who had been in Kibera for at least one month prior to the commencement of survey. Residents who lived in Kibera but not in the slum areas were not included in the survey. Each household unit with its members was the unit of analysis. A

household was variably defined as either a group of people living together under one roof or a housing unit, or people living under one roof and sharing a community of life, by being dependent on common holding as a source of income and food, which normally, but not necessarily, required them to eat from a common pot at all times. Under this set of definitions, household members were those who slept in a housing unit at least four days a week.

4.3.2 Sampling procedure

Probabilistic sampling method was used to determine which household to include in the sample. The sampling frame and household samples were developed based on the National Sample Survey and Evaluation Program (NASSEP III) of the Kenya Bureau of Statistics (KNBS) with the assistance of a sampling experts from the KNBS who were familiar with Kibera slum household listings. The EAs were formed to cover an average of 100 to 150 households, in the rural and urban areas, respectively. However, in this survey a measure of size (MoS) of 100 households in an EA was adopted.

A sampling frame did not exist to permit selection of a representative sample. It was therefore necessary to construct one based on the available census data. Enumeration areas (EA) based on the 1999 population and housing census formed the primary sampling units (PSUs) where a sample of 35 EAs was selected. Using the PPS (probability proportional to size) method (number of EAs Varied in each Sub-location), the 35 EAs were allocated to each sub-location as shown in tableA1

During the counts by KNBS experts, an EAs with 50–149 households were taken to form a cluster. EAs with less than 50 households were merged with the neighboring ones to constitute a cluster. EAs with more than 149 households were divided into equal parts and one segment selected randomly to form a cluster. Once the clusters were identified, a complete listing was done. This involved physical numbering of structures belonging to households within the selected EA.

4.3.3 Sample Size

To arrive at the desired number of observations in the sample, the Yamane (1967) formula to calculate sample sizes was used with a precision level of 0 .045. The Yamane

technique is suitable for this particular study due to its power to generate a large sample on which multiple regression analysis can be applied. The Yamane formula is of the form:

$n = N/ N+ N (e)^2$

Where,

n is the sample size

N is the population

e is the level of precision

The number of households in Kibera at the time of the survey was about 140,000 with a population of about 700,000 people. We used the household as our unit of analysis in order to determine the number of households to be incorporated in the sample.

Applying Yamane (1967:886) formula we determined our sample size, n as follows;

$n = 140,000/140,000+ 140,000(0.045)^2$, which yielded a sample of 492 households.

The sample of 492 households was allocated proportionately to the population of EAs. Each of the 35 EAs provided 14 households for the sample. The number of households allocated to each Sub-location is shown in the appendix Table A2.

4.3.4 Selection of the Households

Selection of the households within an EA was using systematic random sampling. The total households found after the listing in each EA was divided by 14 to get a sampling interval. A random number was selected and multiplied by the resulting sampling interval to arrive at the random start which constituted the 1st household. The 2nd household was selected by adding the sampling interval to the 1st one. The procedure was repeated until the 14th household was selected. The selection of the households was done immediately after the listing exercise.

4.3.5 Data Collection

Before embarking on the actual data collection, research supervisors, and research assistants were trained on the use of the instruments of data collection. This was done during the pilot study, where the same team was used to pre-test the questionnaires. This ensured that the instrument was clearly understood and any area of ambiguity in the instrument was addressed.

The supervisors and research assistants were selected with the assistance of KNBS staff. The KNBS was involved to address the problems noted during the reconnaissance study, for example, the suspicion of slum residents and difficulties of accessing slum areas. The KNBS identified supervisors and research assistants who were familiar with Kibera slum area.

Armed with the research authorization from ministry of education, I was able to introduce my self and my research team to the area administration, that is, district officer and the chiefs. This was to avoid any suspicions or problems that could have arisen during the data collection exercise. Again, it being an electioneering period, it was crucial to inform the area administration about my research to avoid research team being associated with political campaigns. The Kibera administration gave me and my team, a good insight on how to approach the process of data collection at period. They connected with elders from the villages who introduced us to the sampled households.

As suggested by the area administration, each research assistant was attached to an elder in each enumeration area (EAs). This was aimed at facilitating the data collection process. The supervisor's role was mainly to assign the EAs to the research assistant, to ensure that the questionnaires for the day were well done, and to inform me any difficulties that were encountered during the process. I too participated fully in data collection exercise.

Apart from filling up the questionnaires, we observed and noted any health facilities around the area of data collection.

4.3.6 Data Collection Challenges

The data collection task faced four main obstacles

Suspicion

The data collection exercise was preceded by a period of crackdown on illegal connections of social amenities such as water and electricity in the slum area. This meant that the residents were suspicious of anybody who was new to the area. Some residents thought that our survey was intended to unearth health providers who were operating illegally or who were not qualified. This feeling was as a result of a crackdown on illegal health providers that had been

carried out by the Kenya Medical Association in a neighboring location. The residents were thus unwilling to have any form of interaction with visitors to the area.

Accessibility

The housing units in the area appeared very similar and there were no major land marks that could help identify oneset of enumeration area from another. Accessibility was made more complicated by the unanticipated rainy period, which made the slum area almost inaccessible due to very poor drainage. This slowed the process of data collection considerably.

Over-researched Area

The sample household had previously received frequent visitors asking questions related to their lives and life lihood. In many cases, the residents expected some form of reward after the interviews, while in other cases they felt they were being exploited. This experience affected the extent to which households cooperated during the interviews.

Absenteeism of household members during weekdays

Sometimes there was a problem of contacting the sampled members of the household during the working days. This was due to the fact that during theweek days, some of the household members were working outside the slum areas.

4.3.7 Resolving the Challenges

To solve the problem of suspicion and inaccessibility, Kibera administration attached each research assistant to an elder. An elder was a person in each village who was known by the chief as having stayed in the slum area for some time, and who commanded some respect among the residents of the area. Moreover, all research assistants were recruited from the slum locations in which they conducted interviews. Before the start of the interview, the elder explained the purpose and importance of the survey to the household. The introduction by the elder convinced the households that the survey was not intended to interfere with or probe into the slum life. It was clear that some of the households had undergone through rigors of long interviews for they were unwilling to consent to the interviews. However, once they were assured that the interview

would last for a short time, say one hour, they were receptive, and seemed to forget about the time issue as the discussion progressed.

The problem of the unavailability of the household was addressed by extending the survey period to seven days a week. This meant that the household members not found at home during the week days were visited on either Saturday or Sunday. In some other cases, elders were used to establish the availability of some of those who were absent during our visits to a household and to make appointments for an interview. Although this worked well, delays in completing such interviews were significant.

4.4 Data Sourcesand Description of the Variables

The data were collected in Kibera slum located in the heart of the Nairobi City. Data were collected on the use of health facilities in and around the slum area. We collected information on quality of health care at a facility level as opposed to data on perceived quality of care typically collected from households.

In order to strengthen the data from the household survey, some six focused group discussion conducted. The information from FGD centered on perceived quality of services, trust that residents of Kibera had with the services available at the health facilities.

To summarize , the survey collected data on types of health facilities in and around the slum region, accessibility to these facilities in terms of distance, travel time, and price of services, household and personal characteristics such as household size, household income, age of respondents and education; facility characteristics such as availability of drugs, and medical equipment, nature of customer care, number of visit to health facilities by household members, and information on payment arrangements, and service quality.

4.4.1 Variable Description

Health facilities

Health facilities were grouped into two major categories, namely, self care and formal care. Formal care facilities were classified into hospital and non-hospital facilities. The hospital category was further classified into public hospitals and non-public hospitals, while non- hospital facilities were classified into public clinics and non-public clinics. We hypothesis an increase in

the probability of hospital visits for more severe ailments, while the less severe ailments are assured to attract a higher probability of non-hospital visits.

Access variables

Access is considered in physical and financial terms. Distance and travel time are the key indicators of physical access to a health facility. Transport cost and user fees are indicators of financial access. Greater access to health facility is expected to raise the demand for care at the facility.

Individual and household characteristics

The individual characteristics considered included age, gender, education, marital status, religion, employment status, and sector of employment.

Income of the household is proxied by total consumption expenditure per capita, and household wealth is represented by various assets. On the other hand, household structure is variously proxied by household size, number of adults, and number of children.

Facility characteristics or quality

In order to assess the quality of health services provided, an index was constructed out of identified quality indicators such as availability of drugs, injections, and oral hydration, quality index construction method is adopted from Kenkel (1990).Accumulative score for service quality was computed for each facility. The lower the score, the lower the quality of health services provided in that facility relative to other facilities.

Visits to Health Care Providers

A total of visits by the respondents to various health providers were collected. The mean number of visits was computed established for each facility. Further, we constructed an index of social learning within the slum area. This index was for each cluster less the visit for the individual responding to the interviewers' questions. Social learning, as captured by the mean visits to health facilities in a cluster is expected to reduce information asymmetry about the range and quality of the services offered by the available facilities.

Signals on service quality

An index showing the amount of information displayed a facility about the quality of its services was constructed. This index is a proxy for information that individuals possess about the quality of the health services on offer. The information index is based on qualifications of the medical personnels, and the types of health care offered. This index represents signaling by facilities about the quality of their services in line with previous indices as constructed by Kenkel (1990) and Hsiech and Lin (1997).

Payment mechanisms

Data on payment modes was also gathered. The payment mode is represented by a binary variable. The payment mode for health care was either on cash term or on credit basis. This data can help in establish the role of physician's effort toward assuring household that their service is of superior quality. Credit extension to patients is expected to raise probability of visits to health facilities. Credit extension could also be a signal of service quality as in traditional healers markets studied by leonard (2003) because successfully treated patients are likely to make repeat visits to a facility and repay earlier loans after observing a cure.

Patient Trust in Provider

Data on whether the household had trust in health care provider was collected. Trust is measured as a binary quantity. Patients expressing trust in a certain health care provider are expected to experience a small degree of information asymmetry with respect to that provider.

4.5 Sample Statistics

4.5.1 Household characteristics

The survey covered 44.5% of males compared to 55.5% of females. Since random sampling technique developed by the Kenya National Central Bureau of Statistics was used to select the sample is a testimony that there are more female than male households in the slum. The mean age of the head of the household is 35.3years, with a household size of approximately 4persons. The majority of household heads(35.6%) had an upper primary education compared to 5.2% with no education, 2.9% with lower primary,23.4% with some secondary, 26.1% with

completed secondary,6.8% with post secondary . In terms of occupation, the majority of the household heads (54.5%) were engaged in the wage employment in the formal and informal sectors. A third of the household head were engaged in self-employment while 12.2% reported to have been unemployed. Christianity was the dominant religion at 83.4%, compared with 15.7% being of Muslims faith. The majority of the household heads were married (72.3%). This percentage is high compared with 21.5% of single, 4.6% of widowed and 1.7% of separated or divorced persons.

Table4.1 below gives a summary of means and standard deviations of the key variables used in analysis

Table 4.1: Summary Statistics

Variable	No of observation	mean	Standard deviation	min	max
Completed Years of schooling	483	9.904	4.078	0	19
Length of stay in the house in months	480	125.56	9.76	1	660
Size oh the household(number)	483	3.98	1.95	1	9
Distance to health facility in km	483	.05	.37	.01	1.5
Approximate time taken to the nearest health facility in minutes	483	5	.45	.1	10
Distance to the visited health facility in km	399	1.73	1.89	.1	9
Time taken to visited health facility in minutes	399	17.89	20.084	.1	120
Cost of treatment in Kenyan shillings(consultancy fee)	399	194	304.93	0	800
Number of visit made to health facility per a year	398	1.7	1.85	1	24
Approximate waiting time at the health facility visited in minutes	399	63.0725	79.288	0	360

Rental income per month in Kenya Shillings.	429	1164.809	4121.685	0	30,000
Income per month in Kenya Shillings	483	10718.07	7153.826	1000	50,000
Acreage of land holding in the slum or elsewhere in the country	483	1.7	2.936	0	30
Age of the head of the household	483	35.30	10.4438	17	73
Total expenditure per month in KShillings	483	9088.454	4976.34	2470	48,300
Number of people depending on the household income	483	4.316	2.62	1	17
Age of patient in years	400	17.35	14.63	1	89
information score	483	2.63	1.7	0	6
Trust Index	483	11.79	6.30	0	20
Quality of health facility visited. Scored from the facility.	483	63.2	36.02	0	106
User fees(Kenya Shillings	483	933.33	2134.43	0	50000

4.5.2 Health status and health care seeking behavior

Out of 483 households interviewed in the survey, 84 reported having not sought for medical care at a health facility. The period of recall for the study was the last 6 months which is taken in the literature as a good reference point because it ensures a reasonable recall interval. This group of 84 households was considered including those who engaged in self-treatment. The group relied on home treatment, which included previous purchased drugs, pharmacies, traditional healers and prayers meeting.

At the time of interview, 36% of the households reported having somebody sick in the house as opposed to 64% without. Table4.2 does not include health status of the households at the day of the interview. It shows households who said there was no incidence of sickness at the interview day. The response comes from the 64% of the households who said they did not have a sick member that day. When this is compared with frequencies at which the medical care from

the health facility was sought (Table4.2), it becomes clear that not all those who reported illness sought for medical care.

Table4.2: Last time someone was sick in the household.

Last time someone was sick in the household	frequency	Valid percentage	Cumulative percentage
Several days ago	66	19.8	19.8
Several weeks ago	109	32.6	52.4
Several months ago	88	26.3	78.7
Several years ago	71	21.3	100

The table indicates that 32.6% of the respondents sought for medical care within several weeks of the recall period. As the period of recall stretches to several years, there is adecline in reporting incidence of sickness. There is some consistency in the reporting sickness and seeking medical care. Notably, those who reported having sought medical care within several weeks of the recall period coincide to some extent with those who reported sickness at around the same period. The fact that seeking for medical care was referenced to a period of up to six months could explain its divergence from a larger period of recall in shown in table5 for several years ago. It is natural for people not to have vivid memory a sickness that occurred several years ago unless it was generally very acute.

Adults between the ages of 18-65years are cited as the most prone to illness (41.4%).The sickness frequency for infants less than 5years old was 32.7%, for children (6-12years) was 17%., for youth (13-18years) was 5.8%, while for the elderly (above 65 years) was 2.7%. This frequency pattern to a large extent illuminates the age composition within sample households in which the majority of individuals are aged between 18-45 years.

Table4.3 shows the specific health facility categories visited by those who sought for medical care in the event of illness. Private clinic alone was visited by 48% of the respondents. Private clinics and private hospitals were visited by about 58% of the respondents while the rest (42%) visited public health facilities.

Table4.3:Categories of health facilities visited

Type of health facility	frequency	Valid percentage	Cumulative percentage
Public clinics	72	18.0	18
Private clinics	193	48.4	16.4
Public hospital	97	24.3	90.7
Private hospital	37	9.3	100

Though most of the government health facilities in the survey area are at the level of clinics, it is clear from table4.3 that public hospitals have a higher intensity of visits than public clinics. This reinforces the fact that after the household has failed to get a positive outcome from the private clinics there is a high likelihood that it will turn to a public hospital. Private hospitals are the least visited perhaps due to prohibitive costs of treatment at these facilities.

4.5.3 Incidence of Diseases

Table 4.4 reports incidence of main diseases in Kibera slum. Malaria emerges as the leading health hazard in the area, followed by cough, cold, and fever. Typhoid, diarrhea, vomiting and HIV follows in that order. Though the HIV incidence appears to be too low, this could be as a result of stigimasition related to the reporting of the this disease. The existing literature shows that HIV /AIDs in Kibera (GOK 2005) is much higher than what our finding shows.

Table 4.4 Summary of the Diseases reported in Kibera

Type of diseases	percentage
Malaria	44.7
Cough, cold and fever	10.7
Typhoid	10

Diarrhea and vomiting	7
H.I.V/AIDs	5
Others	25.6

Source: Survey 2008

Table 4.5 Definitions of Variables used in the regression models

Variables	Definitions
Health facility dummies	Dependent variables: include public clinics, private clinics, and private hospitals.
Self-treatment dummy	Dependent variable which serves as the comparison treatment option. This option includes self-medication, advice from other household members, friends, remedies from shops, and treatment from non-medical practitioners.
User fees	The cost of treatment in the visited health facility in monetary terms, including the consultation, and cost of treatment and drugs.
Distance	Distance to the nearest health facility, in kilometers.
Quality of a health facility	An index derived from measures obtained from facility questionnaires containing information on relationship to agreed standard for what constitutes good quality. Data on types of drugs, proportion of professionally trained staff, and availability of health inputs are among the variables used to construct this index.
Sex	A dummy variable: male = 1 female = 0
Age	Age in years for all the individuals in the household
Health Information score	An index constructed from the qualitative information given by respondents about qualification of health personnel, Advertisements at facilities, type of treatment received, consultation charges, membership to insurance schemes, availability of immunization services, and whether a health facility was licensed.
Trust index	An index constructed from information given by respondents about the degree to which respondents trusted health care providers
Household size	Number of household members

Occupation dummies	1= formal employment, 0= otherwise
Acreage	land holding in acreages either in urban center or elsewhere by the household
Education	Years of completed schooling.

CHAPTER FIVE: ESTIMATION RESULTS

5.1 Introduction

This chapter discusses the regression results. It begins with a presentation demand parameters derived from the discrete choice methods discussed in chapter4. Estimates of marginal effects from some of these models are also presented. Price elasticity of demand and Simulation results conclude the chapter.

5.2 Conditional Logit Results

The results for conditional logit model are presented in table5.1 below. The results are for conditional probability of the patient visiting public health facilities and private health facilities relative to self-treatment. User fees, distance and quality of care are the generic variables characterizing all the health providers. All other variables are interacted with both the public and private health facilities but not with the reference option, which in this case, is self-treatment.

Table 5.1: Parameter Estimates of Conditional Logit Model of Demand for Health Care

. Variables	Coefficients	*t*-statistic
User fees	-.0041863	-5.90
Distance	-.0801649	-1.00
Health facility quality (higher index indicates better quality)	.0264126	2.84
Sex*private facility	-2.02183	-1.44
Sex*public facility	-1.475443	-1.01
Age*private facility	.0654842	0.67
Age*public facility	.038392	1.01
Health information index*private facility	5.26741	4.79
Health informationindex* public facility	2.392821	2.26
Trust index* private facility	.1101576	1.23
Trust index*public facility	-.1041239	-0.99

Household size*private facility	.195479	0.49
Household size*public facility	.487256	1.23
Acreage* private facility	.1388684	0.47
Acreage* public facility	-.153051	-0.54
Occupation*private facility	-.3837539	-0.81
Occupation*public facility	.3027083	0.67
Education* private facility	-1.135815	-2.82
Education* public facility	-.4864993	-1.31
Log likelihood -521.28053, LR chi2(10) = 512.16 Pseudo R2 = .3294 Prob>chi2 = 0.0000 Number of observation 2415		

Discussion of Results

The dependent variable in table 5.1 is choice of a health care provider. The conditional logit model estimated has three lines of groupings with each group comprising its sub-group. The first line comprises public facilities, which include public clinics and public hospitals. The private health facility category is the second grouping, with its sub-group including private clinics and private hospitals. The third category is self- treatment which includes households who sought heath care from traditional healers, chemists, shops or faith healers. Self-treatment is the comparison mode.

The estimation results show that the user fee is a significant determinant of demand for health care in slum areas. The coefficient on user fees is negative, suggesting that on average, higher user fee charges reduce the probability of visiting any of the health facilities in the slum

areas. This finding is consistent with other studies done in rural Kenya(seeMwabu,1989; Mwabu and Wang'ombe, 1997;Mwabu etal, 1995).

Distance does not seem to be a significant determinant of demand for health care, but has the expected negative sign suggesting a lower probability of seeking health care as distance increases. The main reason why distance appears not to matter could be that Kibera slum is well served with health facilities.

The coefficient on the index of the quality of service offered at health facility supports numerous findings in the literature that quality of the facility significantly affects the demand for health care (Mwabu et al, 1993; Sahn et al, 2003; Gertler and Van der Gaag, 1990). In particular, availability of drugs and other related health inputs attract patients to a facility.

Schooling in this specification has no effect on health care demand. The size of the household though not a key factor in this model had a positive effect on visit probabilities. Unlike in most studies, it appears that a large household increases the probability of seeking health care from a formal health facility. The explanation is tied to the fact that, the larger the number of active members in a household, the more likely that individuals from that household will turn away from self-medication (Bolduc et al,1996). By pooling resources, larger households can offer some form of insurance to its members and afford better care at formal health facilities than at informal sources of care.

Age is not a strong determinant of health care demand according to results from this model. Though the magnitude of coefficient is low, it has a positive sign, implying a high probability of visiting health facility as age increases.

Acreage in our model is a proxy for wealth of a household. The conditional logit model parameter estimation returned a non- significant coefficient for the acreage variable. The probability of seeking health care from a private facility increases with asset possessions, while decreasing at a public facility.

The probability of seeking health care from either public or private facilities is influenced by employment status of the household member. Persons who were employed had a lower probability of seeking health care from the public health facility. They had a higher probability of visiting private health facilities relative to self-treatment. On the other hand, having no job increased the probability of seeking health care from a public health facility. The main issue in

the slums is affordability of care. In some public health facilities, the user fee was as low as Ksh 20(for buying a visitation a card) but even this was not affordable by many households.

The parameter estimates for the sex dummy show that being male decreases the probability of seeking health care at both the public and private health facility. The gender dummy suggests that males are more likely to use traditional and other non- formal health sources of medical care. The result is at odds with most studies in the literature, which report that being male increases the probability of a visit to a private facility, with the reasoning that the males control household resources. While the resource control argument may apply in rural areas it does not seem to apply in slums where women occupy a dominant role in informal activities, commonly found in slums. Moreover the findings are consistent with the belief in some cultures that females are more sensitive to their health status relative to males.

Information about the health care providers is key in determining the probability of a visit to health facilities. Having more information about an aspect of a facility that enhances service quality at a facility increases the probability of the facility being used in the event of illness. The estimate for the coefficient of this variable is positive and highly statistically significant. Information about the facility having qualified staff having drugs, being able to accept payment via a government insurance scheme and the facility being open when care is needed, are among the key factors that attract patients to a health facility. If patients have adequate information about these factors, their probability of choosing self treatment decreases by a very big margin. The kind of information that a household possess about a provider significantly affect the probability of a visit to that provider in the event of illness or injury.

Trust, which is measured, using an index that indicates the extent to which households trust health care providers, increases the probability of visiting private facilities. The fact that private facilities strive to create a personal touch with patients, partly for profit motive, could be a key reason for the greater degree of trust associated with these facilities. The probability of seeking health care at a public health facility is negatively associated with the trust variable. This relationship is perhaps attributable to the correlation of trust with information about inadequate availability of drugs at the public health facilities. These results suggest that it might take time before a trusting relationship can develop between the public and government health facilities, due to negative experience with these facilities in the past.

5.3 Nested Logit Results

The nested logit results are reported in Table5.2. The nesting is done, firstly, to test whether the facilities in the nest are independent of facilities in other nests. This is done by establishing whether the inclusive value parameter from each respective group or level, has a coefficient value less than one. If the coefficient on inclusive parameter(i.e., the dissimilarity parameter), is less than one, then we reject homoscedasticity assumption and accept the assumption of correlated error terms within a given nest. This conclusion implies lack of independence within a facilities. If on the other hand, the inclusive value parameter(logsum parameter), is one or greater than one, homoscedasticity assumption is accepted and conditional logit estimation should thus yield better results than those of the nested logit.

Table5.2: Nested Multinomial Logit: Private Facility and Public facility

Variables	Coefficients	*t*-score
Distance	-.0521046	0.80
Facility quality index	.0274927	2.75
User fees	-.0042615	5.81
Acreage*private facility	.2693737	2.49
Household size*private facility	-.569857	0.35
sex*private facility	.7181277	1.57
occupation* private facility	.1831586	1.06
Education* private	-.0109326	0.17

facility		
Age *private facility	.0037422	1.06
serviceInformation index*private facility	3.156566	9.52
Trust index * private facility	-.051015	0.74
Inclusive value parameters(i.e. coefficients on inclusive value variables)		
Private facilitiesNest	.952351	2.26
Public facilitiesNest[1]	.247943	0.004
[1]reference option for the nest		
Levels = 2	Number of obs = 2415	
Dependent variable = chosen facility	LR chi2(13)= 122.7264	
Log likelihood = -715.9953	Prob > chi2 = 0.0000	

Discussion of the results

The results from table 5.2 support a downward sloping demand curve (see Sahn et al 2003). The user fees has the expected negative sign that is statistically significant. The nested logit model has coefficient for the inclusive value variable that is less than one in both nests though only significant for the private health facility. Although distance has negative sign for this nest, it is not significant implying that on average patients visits to the private facilities is not affected by distance. Wealth proxied by acreage had a positive sign for private facilities relative to public facilities. This concurs with the results for the conditional logit model. This has the implications that asset has a positive impact on visits to a private facility. Our generic variables

which includes distance, quality of the health facility, and user fees carries the same sign in the nested logit as in the conditional logit model. The nested logit results do not contradict the results from other discrete models discussed in this paper, meaning that these methods have a lot in common. The main difference in terms of results will depend on the underlying assumptions and the robustness of the estimated parameters. In particular, estimation of the nested logit parameters takes into account the correlation among facility subgroups, while estimation of conditional logit ignores this correlation. This is a major difference in the two models. The intuition behind the signs and magnitudes these our variables in the models is discussed under multinomial logit and multinomial probit in the section that follows.

5.4 Multinomial Logit and ProbitResults

The multinomial logit model assumes a case of homoscedasticity in disturbance terms of the utilities associated with health facilities. The assumption is that the disturbance terms are distributed as Weibull (Mwabu, 1989b). On the other hand,the multinomial probit model assumes that the disturbance terms follow a normal distribution(see Bolduc et al, 1996).Thus the multinomial probit relaxes the IIA assumption characterizing the multinomial logit. Thus the multionomial probit parameters are free from the biases due to the IIA assumption. The results in Tables 5.3 and 5.4indicate that the probit model corrects for the IIA biases to a considerable extent.

Table 5.3: Flexible Multinomial Logit Parameter Estimates (Absolute t-statistics in Parentheses)

Variables	Public clinics	Private clinics	Public hospitals	Private hospitals
	Coefficients estimated	Coefficients estimates	Coefficients estimate	Coefficients estimates
User fees	-.0047696 (11.94)	-.0005119 (6.02)	-.00010331 (2.02)	-.0001102 (2.08)
Facility quality index(the higher the index, the better	.3341173 (1.97)	.9751281 (5.41)	.2050169 (1.21)	1.002703 (5.42)

the quality)				
Waiting time	.0347823 (2.25)	.028216 (1.83)	.04250011 (2.75)	.0267459 (1.73)
Service information index (thehigher the index the better the quality)	1.171722 (2.33)	5.156972 (9.52)	1.084405 (3.67)	6.339419 (11.33)
Acreage	-.7214043 (2.72)	-2.082656 (0.95)	-.6349885 (2.42)	-.2785803 (1.05)
Trust index(the greater the trust , the index)	.5901797 (5.61)	.5035723 (4.53)	.6404762 (5.98)	.5568273 (4.90)
Distance	-2.502082 (2.22)	-2.082656 (1.78)	-2.233896 (1.99)	-1.656626 (1.39)
Household size	1.398719 (4.37)	1.131099 (3.48)	1.08512 (3.41)	.911039 (2.76)
Occupation(1=formal employment)	-.0712954 (0.29)	.2995476 (1.16)	.0449243 (0.19)	.2270215 (0.85)
Education	.3873954 (2.95)	.2788896 (2.05)	.3378681 (2.56)	.2561829 (1.86)
Age	.10030717 (2.37)	.1294236 (2.88)	.1223703 (2.87)	.16021704 (3.48)
Sex (1=male)	-2.412717 (2.47)	-1.781863 (1.78)	-2.638726 (-2.70)	-1.367104 (1.34)
Constant	-15.71434 (4.77)	-32.49531 (8.95)	-17.77896 (-5.32)	-40.84233 (10.88)
Log-likelihood=-1039.0756 ; LR chi2(44) =5033.95 ; Number of observation=2415				

Table 5.4: Multinomial Probit Parameter Estimates (Absolute t-statistics in Parentheses)

Variables	Public clinic	Private clinics	Public hospitals	Private hospital
	Coefficients	Coefficients	Coefficients	Coefficients
User fees	-.0024255 (14.15)	-.0002908 (7.07)	-.0000742 (2.58)	-.0000775 (2.60)
Facility quality index (increases with quality)	.2587349 (2.42)	.7040708 (6.11)	.1360388 (1.26)	.7008101 (5.86)
Waiting time	.0267798 (2.83)	.0206639 (2.19)	.0318304 (3.37)	.0193221 (2.04)
Healthinformation index	.7069139 (2.45)	3.53655 (11.29)	1.2477 (4.33)	4.351906 (13.14)
Acreage	-.5226657 (3.29)	-.2003306 (1.28)	-.4423209 (2.83)	-.2330826 (1.48)
Trustindex (increases with trust)	.3904678 (6.44)	.3473449 (5.33)	.446738 (7.11)	.397244 (5.89)
Distance	-1.959018 (2.79)	-1.75095 (2.41)	-5.55266 (2.22)	-1.469643 (1.97)
Household size	1.083069 (5.95)	.8382298 (4.57)	.787664 (4.38)	.6851694 (3.65)
Occupation(1=formal employment)	-.1358581 (0.93)	.1987752 (1.26)	-.0179633 (0.12)	.1198647 (0.73)
Education	.2972528 (2.95)	.214329 (2.51)	.2534123 (3.06)	.2059749 (2.38)
Age	.10030717 (2.37)	.874665 (3.01)	.0880447 (3.20)	.112462481 (3.76)

Sex(1=male)	-2.412717 (2.37)	-.8678854 (1.49)	-1.584831 (2.80)	-.4762481 (0.80)
Constant	-15.71434 (4.77)	-23.1153 (10.20)	-13.01778 (6.24)	-29.08893 (12.24)
Log-likelihood=-1085.3693; Wald Chi2(44) = 828.25 Number of observation 2415				

Discussion of results

The two tables (Tables 5.3 and 5.4)present the parameter estimates of the two specifications, namely, the multinomial logit (ML) and multinomial probit (MP) models. Though the two tables give similar signs for each provider's variables, probit results are more improved interms of level of significance for all the covariates under investigation. As noted earlier, multinomial logit imposes the property of the "independence of irrelevant alternatives". This property is a consequence of the implied assumption of no correlation between the unobservables characterizing the alternative sources of treatment or the error terms of utilities associated with these alternatives. On the other hand, multinomial probit relaxes this assumption since it allows for correlation between all alternatives, since unobservables at a given facility are no longer independent of those characterizing other facilities.

In absolute terms, ML logits coefficients seem larger than MP coefficients in almost all the variables across health care facilities. This is an indication that ML overestimates the extent of influence of variables in the stated model. It also suggests that most of the variables in ML were positively correlated with unobservable further strengthening the impact of IIA assumption.

In Tables 5.3 and5.4, the statistically significant parameters are essentially the same across specifications. The price has a negative and significant impact on choice of a given health facility and is of the same order of magnitude both in ML and MP specifications. These results mimic the findings in Bolduc et al(1996) who found price in both multinomial logit, and probit models to have a negative and significant impact on treatment choice probabilities in Benin.

Distance

Distance has significant and negative impact on the choice of a health facility. The MP has higher *t*-ratios compared with ML for the distance variable across all alternatives. Increasing distance would result in a household opting for self-treatment, a result also reported by Mwabu et al (1993) and Cisse (2006). The impact of distance is higher at the public facilities. In the ML models, distance carries a negative coefficient which is statistically signed in both private clinics and private hospitals. The sign for the distance coefficient can be explained by appealing to the monetary cost of treatment. An increase in distance implies paying some cost to travel to the source of treatment as opposed to seeking self treatment. There is a sense in which distance adds to the monetary cost of treatment. Given the fact that those who visit private health facilities have already made a decision to spend extra money on treatment, the impact of distance on the choice probability for private providers should not affect their choice probabilities substantially. However, assuming that visiting public facility is driven by low user fees, holding other factors constant, an increase in distance is synonymous to increasing price (i.e., through travel cost),and has the effect of lowering the probability of visiting a public facility. This result differs from that of Bolduc et al (1996) who used travel time as an indicator of access to medical care, and found it to be implausibly positively correlated with the probability of seeking health care at both public and private facilities.

Quality of Health Care

Quality of the health care has a positive impact on demand for health care. The impact is more pronounced in the private health facilities in both the ML and the MP models. On the other hand, the impact is smaller at public hospitals. This weak responsiveness of demand to quality at public government hospitals is consistent in both ML and MP models. Private health facilities are profit motivated so that there is a focus in improving service quality to attract patients. The result could be indicating that quality is higher at private clinics. The finding is in agreement with the studies by Sahn etal (2003) in Tanzania, Mwabu et al(1993) in Kenya, and Ellis et al(1994) in Egypt who also found that medical quality, assessed in terms of both health staff qualifications and by availability of drugs increases the probability of a visit to both private clinics and public hospitals. The fact that service information is key to determining the demand

for health care implies that information about quality of care in the study area is being transmitted through channels that advertise the quality aspects better at private health facilities. The past experience in Kenyan public health facilities of persistent lack of drugs and shortages of inpatient doctors and nurses could still be in the memories of the majority of the households in the Kibera slums, discouraging them from using public facilities which currently offer good quality services, but about which they are unaware of. Incidentally, what attracts the patients to public health facilities at the moment could be the low user-fees at these clinics. It appears that self-treatment (consisting of remedies at shops, pharmacies, chemists, and at faith-meetings) could also be more expensive, and lacking in quality, compared to what is available at both public and private facilities.

Trust

Patients' trust(McGuire, 1982)in the health providers is a significant determinant of the demand for health care in the slum areas of Kibera. Both ML and MP estimates show a very significant impact of trust on treatment choice in all facilities and in all specifications. The implication of this is that the more trusting the relationship the provider builds with their patients, the higher the probability of a visit to that provider in the event of illness or injury. Trust in this context means a lasting relationship between the health provider and the household in which it is understood by the household members that quality care will be offered by the provider when needed. This relationship is underpinned by qualitative utility that is not measureable. This qualitative utility, like other utility indices depends on characteristics of the patient and the nature of the agency relationship between the patient and the health provider. Apart from a business relationship resting on credit for example, trust also depends on the patient's health outcome after visiting a health provider. The campaign against use of over-the-counter drugs without the prescription of a physician is likely to erode trust in self-treatment and shift demand to the formal health care system. Though public facilities usually deliver quality health care at slow pace, there is strong perception in Kibera slums that it is the government clinics that should lead in extending modern care to the public. A high positive coefficient on the trust variable within the public health facility system supports this conjecture. It is worth noting that having a lot of trust on a provider can be a cause of poor health outcome as supported by the binary probit model on household sickness (see Appendix Table 3). The coefficient for trust

variable is positive and statistically significant implying that having someone sick in the household is associated with a strong trusting relation to a health care provider.

Waiting time

The waiting time coefficients are higher and statistically significant in ML than MP models across all alternatives and consistently positive. This implies that the time spent waiting for treatment is associated with additional utility and that the probability of choosing any health facility increases with time spent waiting for treatment. This sounds unconvincing because the result suggests that there is no opportunity cost for waiting for treatment at a facility. However, there are several plausible reasons for a positive coefficient on waiting time. First, the marginal utility of quality emanating from the contact with a health provider could be much higher than the disutility that is resulting from time spent on waiting for treatment. So long as the patient can observe the quality of health care provided by the health facility, waiting time will be negatively related to self-treatment, where quality is assumed to be low. It is important to stress that the coefficient on waiting time is relative to that for self-treatment. Second, trust is another reason that may lead waiting time to have a positive coefficient. The results for the public health facilities and particularly, the public hospitals do not strong statistically significant parameters for quality, yet the waiting time coefficient is positive and statistically significant. The trust index coefficient at public hospitals is the most significant of all the other coefficients. The marginal benefit that a patient gets from trust is a function of the interaction of trust with waiting time at the facility. Individuals would prefer to wait for treatment from a health provider they trust. Third, there is no direct opportunity cost for a seriously sick person because the person cannot work, except of course for persons accompanying the patient. Once sick the main decision to make is on mode of treatment, in which case, each mode has its cost. The level of income dictates choice. For low income groups, waiting time in a public facility, where user fees are low, can be taken as a boost to the net income (income after paying the user fees).This situation implies that the marginal net benefit from waiting time will be higher at a health facility witha low cost of treatment, such as a public clinic. This waiting behavior is synonymous with patient using time as a resource to pay for quality where fees are low.

Service Information

The information set a patient has about a health facility and the services offers has a significant impact on choice of a health facility. In both ML and MP models, the coefficient on the service information index is statistically significant, particularly at private health facilities. It appears that private health facilities benefit more from the information set that households possess about the quality of health care being offered in the study area. This finding is in line with that of Thompson (2003), who found that lack of adequate health information was associated with variations in health care utilization at various health facilities, and especially between rural and urban sector when using Kazakhan data in analyzing health-seeking behavior of rural and urban households. Our results also find support in Kenkel (1990) who using probit model, found the information patients possess on services influences health care seeking behavior. The finding by Hsiech and Lin (1997) that demand for health care for elderly in Taiwan needs to be interpreted with caution due to the likelihood of selection bias in their study. However, their finding is in line with our result that the information available about health services is a key determinant of health care demand.

Gender

The coefficient on gender dummy is negative and statistically significant in public health facilities suggesting that being male decreases the likelihoodof visiting public facilities relative to self-treatment. It is also the case that females are more likely to visit public health facilities than their male counterparts. This finding supports the hypothesis that females are more sensitive to their health status more than men. The coefficient on the gender dummy in private facility is negative and statistically insignificant. Again, this has the implication that males in slum areas are less likely to seek for medical care from the private facility relative to self-treatment. Overall, the females are more likely to seek out professional healthcare compared their males. This finding concurs with Mwabu et.al (1993) who found women to be more likely to consult all types of providers of modern care relative to self–treatment. Large negative and statistically significant coefficients for gender dummy in public clinics and public hospitals compared to low and insignificant coefficients in private clinics and private hospitals in both ML and MP models suggest that women are less endowed with economic resources to seek medical care in private

facilities.Sahn etal (2003) report gender bias using Tanzanian data where men tended to visit public health facilities with lower frequencies compared to women. Our findings need to be interpreted with caution because the data did not separate out normal pregnancy related visits from other visits, and thus could affect the female frequencies of visiting private and public clinics.

Size of the household

The effect of the size of household on choice of health care is positive and largely significant in both ML and MP models. Having a large family increases the probability of visiting both public and private health facilities compared to self-treatment. The intuition behind this comes from could be drawn from Bolduc et al (1996) who argued that the more active members there are in a household, the more likely individuals will turn away from self-medication. A large household could pool resources and thus offer some form of insurance to its members, enabling them to afford better care.

While we would have expected persons from larger households to be less likely to seek care, because of competition for resources in the household, our finding rejects this expectation and is in support of Sahn etal (2003), and Bolduc etal (1996) who found household size to be positively related to probability of seeking health care from the formal health care system. Sahn et al, especially, found household size to positively affect the demand for health care in the public facilities, a finding that is backed up by our MP results. Another plausible reason is that in a large household there is less attention to members of the household in terms of their nutritional needs and this makes them prone illness, increasing probability of using medical care.

Acreage

The size and magnitude of acreage coefficient is negative and statistically strong in both public clinics and public hospitals. This result supports the idea that people with more resources are less likely to seek medical care from a public health facility. They have the ability to seek health care from more comparatively expensive sources like private health facilities. Intuitively, this implies that having a strong asset base reduces the chances of visiting public facilities relative to self-treatment, which includes drugs at pharmacies and chemists.

Education

As expected, education has a positive and statistically significant coefficient in all models. This result supports the prediction that educated individuals are more likely to seek out professional heath care relative to self-treatment. The parameter estimates are positive and significant in all health facilities and in both ML and MP models. These results are consistent with many others in the literature. Interestingly, and inconformity with Sahn etal (2003), the rate of increase in demand is greatest for public health facilities than in the private health facilities. Cisse(2006) found education to positively affecting demand for health care. Hutchison (1999) found more educated women to have higher likelihood of seeking health care that less educated ones. This is also inconsonance with the general notion that the pattern of reporting morbidity and contacting a health professional tends to increase with the level of education. The finding has the implication that educated people could distinguish real quality of health care by observing the qualifications of the health providers. A public health facility is guaranteed of quality and trained health personnel, compared with private clinics where the qualification of the health personnel is not readily known. Our findings do not support the widely held perception that a year of schooling reduces the probability of seeking health care from a public health facility relative to self-treatment.

Age and occupation

The effect of age on the demand for health care is significantly positive across all the health facilities indicating that the health-risk effect dominates the lifecycle effect, and thus the probability of using professional health care service relative to self-treatment increases with age. This finding could be confounded by other variables such as education, social learning, and income which are likely to increase with age. For example, the years of schooling and age are much related. Moreover, having stayed in the same area for a long time is likely to improve the information possessed about the social amenities, including health facilities. This finding is supported by survey data where the average stay in Kibera slum is 13years. The finding differs from widespread belief that as people get older, they seek treatment from traditional medical practitioners. The result is in tandem with the fact that the households headed by older people have a higher propensity of seeking professional health care rather than self-medication. This to

a large extent implies that the head of the household still controls economic resources even in a slum environment.

Occupation of the household head did not have a significant impact on the choice of health facility. The sign for parameter estimate was negative for public clinics and implying person in formal employment, preferred public clinics to self-treatment. This is consistent with the widely held assumption that those who are formally employed would prefer professional health care e to self-treatment, especially since they are enrolled in a mandatory health insurance that pays for formal healthcare.

User fees

As expected, the user charges have a negative coefficient which is highly significant, remarkably in all specifications. This contradicts Schwartz et al (1988) and Akin et al (1986) who found user fees to be insignificant determinants of choice of health care providers. Our findings are in line with those reported in Mwabu et al(1995), Yoder(1989), Dow (1995),Cisse (2006) and Mwabu et al(1993) who all found user fees to be key in determining health seeking behavior of sick individuals.

Marginal effects

Table5.5 shows the marginal effects of the independent variables on the choice of medical practitioners, derived from the estimated coefficients for the multinomial probits. Each element in the table can be read as the percentage change in the probability of visiting a practitioner given a unit change in the respective variable from its average value. For this purpose Table5.5 is easy to interpret. The coefficients reported in previous tables provide a sense of the direction of the effects of the covariates on health care seeking behavior but not the magnitudes of the impact of the covariates on visit probabilities, as in Table 6.6.The marginal effects inform on the magnitudes of the impacts of the covariates on probabilities of visiting health facilities in the slum areas studied

Table5.5: Multinomial Probits: Marginal Effects (Absolute t-statistics in Parentheses)

Variables	Public clinics	private clinics	Public hospitals	Private hospitals	Self-treatment
User fees	-.0000878 (4.03)	-.0000561 (3.69)	-.0001427 (7.02)	-.000062 (7.10)	-.000052 (0.89)
Quality	.0017346 (1.66)	.1510512 (10.80)	.1523016 (10.93)	.0031938 (3.35)	-.0002088 (0.88)
Distance	-.006723 (1.08)	.0303035 (0.38)	-.0282701 (0.35)	.0029544 (1.34)	.0010846 (0.93)
Information index	.0311237 (3.31)	.6567835 (10.73)	.6440317 (10.45)	.019733 (3.47)	-.0013612 (0.93)
Acreage	-.0037857 (2.43)	.0764067 (5.26)	-.0742609 (5.05)	.0013782 (2.64)	.0002616 (1.11)
Waiting time	-.00007 (1.78)	-.0027656 (6.38)	.0029183 (6.71)	-0000638 (2.87)	-.000019 (0.94)
Trust index	.00219 (0.35)	.0267016 (2.86)	-.0742609 (2.94)	-.0002447 (1.05)	-.0002973 (0.92)
Education	.0012849 (2.15)	-.0118089 (1.67)	.011046 (1.56)	.0003628 (1.71)	-.0001593 (0.89)
Sex	-.0003002 (-0.08)	.1622686 (3.08)	-.1687619 (3.19)	.0055047 (2.50)	.0012888 (1.06)
Age	-.0004665 (1.72)	.0014788 (0.46)	-.0011502 (0.35)	.0001992 (1.84)	-.0000613 (0.94)
Household	.0058332	.0078517	-0120871	-.0010527	-.000545

size	(2.70)	(0.41)	(0.62)	(1.69)	(0.99)
Occupation	-.003631 (1.98)	.0509165 (2.49)	-.0478559 (2.32)	.0006264 (1.09)	-.000056 (0.49)
Number of obs = 2415; Wald chi2(48) = 797.84, Log likelihood = -1000.1678; Prob > chi2 = 0.0000					

Discussion of Results

Increasing quality by 100% for example, leads to a0.17% increase in public clinics, 15% in private clinics, 15.2% in government hospital and 0.3% in private hospitals. Notably, a shilling increase in user fees in all the facilities will lead to only a very small percentage drop in usage in all the alternatives. This means that demand is highly price inelastic. However, it should be noted that these are semi-elassticities. The magnitude of change in self-treatment has appealing and expected sign though the results are not significant for all the facilities.

The magnitudes of coefficients for distance are not statistically significant though the signs shed some interesting light in that increasing distance to public facilities reduces the probability of visits. This has the implication that distance can deter health care consumption at public health facilities. The argument can be advanced further in that distance will enter into the pricing structure of the alternative health facilities. Thus, given that the majority of those seeking public health cares are in low income groups, there is likelihood for them to opt for self treatment option when the distance to public health facilities increases.

Increasing information about service availability by 10% could have a large effect in all the health facilities. This implies that information about the quality of services offered by the health facility relative to self treatment increases attractiveness of formal sources of care. It can be argued that information variable could be correlated with factors such as the signaling, social learning, variables associated with perceived quality of care.

5.5Price Elasticities and Policy Simulations

In order to establish how a government policy on user fees would affect the demand for health care in a slum environment, we have chosen to change the price of health care in public

hospitals and simulate the effect of such policy on service utilization. The Government can affect the price of private providers by indirectly changing its own price, on the assumption that there is a level of substitution between public health care provision and the private provision.

The elasticities indices are reported in Table 5.6. The table reports both own price elasticities and cross price elasticities. While own price elasticities are reported on the principal diagonal, all the other coefficients represent cross-price elasticities. For example if price at public clinic is increased by 10%, there will be own price elasticity of -24.6% reduction in probability of a visitto a in public clinic. The cross-price elasticities at alternative facilities are: .038 in private clinic, -.239 in public hospitals, .858 in private hospital and 1.621 in self-treatment.

The own price elasticities are negative, as expected. This implies that increasing user fee in each category of heath care provider will lead to decrease in demand for healthcare in that specific provider where price has been increased. The high own price elasticity of demand at public clinics(-2.46) should be noted. This finding indicates that in Kibera slum, residents are highly sensitive to changes in health care prices at public clinics. This argument is in line with Sahn el al (2003) who found low income group in rural Tanzania to be highly sentive to cost of medical care.

Howerver, apart from the case of public clinics, and public hospitals, all the other cross-price elasticities take a positive sign, suggesting that services at various health facilities are substitutes. Cross price elasticities for public clinics and public hospitals support our findings from the nested logit model of close correlation between public clinics and public hospitals. The coefficient for inclusive value variable(the logsum parameter)that is far below one, supporting existence of a nestingstructure between public clinics and public hospitals.

The cross price elasticities reported in Table 5.6 supports the hypotheses of substitution between private and public health facilities as shown by opposite signs for the price coefficients in the two categories of health care facilities.

To gain further insight into the health care seeking behavior of ill individuals, Table5.7 reports the simulation results of decreasing the user fees charged by public hospital by a given percentage. A 10% decrease in public hospital user fees shows a low relative change in probability of seeking health care in the entire set of treatment alternatives. Our earlier inclusive value parameters which is between zero and one, though not very significant, does support the

nesting between public clinics and public hospitals, The simulation results show a strong link between public clinics and public hospitals in the provision of care. This finding is supported by MP estimates, in which unlike the case of entire set of the available alternatives, the relative change in visit probabilities in both public clinic and public hospitals is positive following a rise in fees. This clearly indicates that, the probability of seeking health care in both public clinics and public hospitals increases with a reduction in fees.

Visitation probabilities at privateclinics, private hospitals and at self treatment alternatives decrease very little when user fees are decreased in public facilities. For example a 10% decrease in user fees at government clinics does not have a large negative impact on the demand for healthcare .This result contradicts the work of Bolduc et al (1996) whose finding with Benin data indicated a strong substitutability between government facilities and private health clinics.

Table5.6: Multinomial Probits: own price and cross-price elasticities of demand (t-statistics in parentheses)

Facility type	Public clinics	Private clinics	Public hospitals	Private Hospitals	Self-treatment
Public clinics	-2.46 (8.57)	.038 (0.91)	-.239 (7.05)	.858 (7.23)	1.621 (4.48)
Private clinics	-1.272 (8.53)	-.016 (0.37)	.260 (7.55)	.906 (7.64)	1.673 (4.61)
Public hospitals	-1.748 (8.32)	.076 (1.91)	-.242 (7.55)	.844 (7.73)	1.593 4.60
Private hospitals	-1.375 (8.60)	.057 (1.36)	.236 6.91	-.840 (7.16)	1.599 (4.49)
Self-treatment	-1.444 (8.58)	.040 (0.97)	.240 (7.05)	.860 (7.25)	-1.62 (4.47)

Table5.7:Policy Simulations: Effect on demand of decreasing user fees in public hospitals by 10%

Visits Probabilities	public clinics	private clinic	public hospital	private hospital	self-treatment
Base Probabilities	.046	.343	.611	.002	.0001447
Predicted Probabilities	.0626	.333	.662	. .00198	.0001356
Relative change in probabilities of visiting facilities	.0166	-.01	.051	-.00002	-.000009
% change using base probabilities as references	+36%	-2%	+8%	-1%	-6%

CHAPTERSIX:SUMMARY AND CONCLUSIONS

6.1 Summary and Conclusions

This study has developed a model of demand for health care in a slum setting with the hypothesis that the information available on the health services is a key variable in the determination of health care seeking behavior of the patients. The model was estimated with data from Kibera slum in Nairobi, a large residential area inhabited by low income households.

After estimating the nested logit specification of the demand model, alternative ML and MP models are estimated. The estimation results show that the MP model outperforms other models, in line with results reported earlier by Dow (1999) and Bolduc et al (1996).

In particular, the MP estimates have the advantage that they are derived under the assumption of normal distribution of the unobservables characterizing available treatment alternatives. This assumption permits correction of parameter estimates due to IIA assumption that is in-built in alternative models.

Moreover, the MP estimates allow the extent of substitution across sources of health care to be evaluated. The results from the MP model of demand can reveal how demand patterns across the health care system will change following modification of covariates, of policy relevance, such as the user fees in one sub-system of the health system, e.g., government health faculties.

The information the households possess about the available range of health services were shown to be a key determinant of choice of source of treatment. However, the effect of the service information variable on demand needs to be interpreted with caution because it is likely to be correlated with other factors,such as social learning, signaling, age and education of patients.

Although the coefficient on user fees carries the expected sign, which is statistically significant, its overall marginal effect across facilities is low, indicating that demand for medical treatments in Kibera slum is price inelastic. However this finding varies by type of health facility. The demand for health care at public hospitals for example is highly price elastic(own price elasticity is -2.5), indicating that a small percentage increase in price at these facilities will substantially reduce probability of seeking treatment in hospitals in the event of illness or injury. This result has previously been reported in rural areas in Kenya(Mwabu et al, 1995).

Patients' trust in health care providers is a crucial determinant of demand for health care in Kibera slums. A trusting relationship between the households and health care providers is strongly associated with higher visit probabilities in the event of illness or injury. The widespread belief that women are more likely to seek for medical care find support in data collected from Kibera.

The simulation results indicate that visit probabilities in public clinics and public hospitals are strongly positively correlated. This finding is also confirmed by a positive and statistically significant estimate of the inclusive value parameter (dissimilarity parameter) for public clinics and public hospitals in a nested logit model. The sample data suggest a some complementarity between public clinics and public hospitals in dealing with the health problems of slum residents as the cross-price elasticity between the two sets of facilities is negative and statistically significant. This finding is some suggestive evidence that the referral system in the slums might be functioning reasonably well..Moreover, the complementarity between public hospital and public clinics is further supported by the positive coefficient for on inclusive paramter value for public clinics and public hospitals obtained from the nested model. The magnitude of parameter (which is close to zero) indicates a strong positive correlation in benefits households perceive for treatments at public clinics and government hospitals. The correlation however is statistically insignificant due perhaps to the sample size for this study.

6.2 Policy Implications

The study has yielded results of policy value. The estimation results show that quality and waiting time increase the probability of visits to private and public facilities relative to self treatment. This finding has important policy implications. To start with the result show, increasing the quality of health facilities would be associated with long waiting queues at the facilities. In facilities with low cost of treatment, such as public clinics, quality improvements would increase the waiting lines because people would be willing to pay for quality by waiting longer at the clinics. Ways for managing such lines should be part of quality improvement strategies. Since queues at health facilities carry opportunity costs, measures that improve health

of the household could harm their economic well-being, if implementation of such policies is not properly managed.

Information on health services available in slums has been shown to be an important determinant of demand. This is an interesting and important result, as it shows that public health information campaigns can be used to change patterns of attendance at government clinics. For example the campaigns can be used to increase demand for treatment for common illness, or serious illness such as tuberculosis or HIV/AIDS. The findings also imply that private clinics have the incentive to use advertising campaigns to induce households to over-use health services. In other words, supplier-induced demand can occur due to advertisements for unnecessary treatments.

The study suggests need to develop program on a health information campaign for updating the general public about new innovations and treatments in private health care markets, and public health systems where health service is provided at nominal user fees.

6.3 Suggestions for Areas of Further Research in Demand for Health

The demand for health care services has been studied using an individual as a unit of analysis. There is need to assess the perception of the policy makers on the factors that they belief affect the demand for health care services in rural and urban settings. This will establish the gap that could exist between what individuals considers to be a constraint on seeking health care and what the policy makers considers to be barriers to such care. Public health policies can be implemented to close such gaps

It is important to extend this study into establishing how household deals with their information asymmetry that exists between them and health care providers. In particular, is there social learning in health care markets? How do patients responds to any information signals about quality. A study of cost-effective strategies of extending public health information to the population is needed. There is also a need to complement a qualitative demand study of the type undertaken in this thesis, with an in-depth qualitative investigation of health service utilization.

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This book provides a new insight on the comparisons of discrete choice models. It provides evidence on the fact that using different discrete models yield similar results except by size of coefficients. The chapter on methodology has revisited four econometric models popular in theory of discrete estimation. The main strength of the book lies more in the use of practical approach to using demand for health to argue that one can adopt various discrete models estimation to arrive at the same conclusion for policy. This is not to say that assumption and weakness of the model is not important. The author has highlighted the limitation of each model but has gone further to show that this should not hinder the acceptance of approximated results for policy. Hence this come as a consolation for those who intends to use any of the models discussed model. The book also provides a comprehensive literature on the findings of past researches that used either logits or probit models in the health studies. The clarity of the language makes the book a good read especially for students and researchers interested in the analysis that involves discrete models of more than two categorical variables. The book provides a good guide on the interpretation of maximum likelihood results including practical approach on simulation and price elasticity measure.

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