ESSAYS ON WILLINGNESS AND ABILITY TO PAY FOR HEALTH INSURANCE AMONG INFORMAL SECTOR WORKERS IN SIERRA LEONE

By

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Abstract

Access to health care is a serious problem in Sierra Leone, more so in rural areas where living standards are low and there is absence of health care facilities. Health insurance, it is argued, will play an important role in giving access to medical care and reducing the high out of pocket (OOP) health expenditure, thus preventing unnecessary deaths and increasing well-being. It is however difficult to know the exact value households place on health and health care as they are not generally exchanged in the market place. For this reason, nonmarket valuation is increasingly becoming an important tool for informing policy makers. The Contingent Valuation and Discrete Choice Experiment (DCE) are the most widely used methods. However, due to its increased popularity, the ability to calculate incremental benefit of each attribute used, and it proving to be more appealing, this work therefore used the DCE method to collect data.

This study provides the following: first, a review of the application of DCE to health outcomes including health insurance for the period 1990 – 2013; second it estimates the willingness to pay (WTP) for health insurance; third, it estimates the impact of corruption on participation in health insurance; and finally, it looks at ability to pay (ATP) for health insurance among informal sector workers in Sierra Leone using a DCE method. The four essays/papers (Chapters 2 – 5) represent the main outcomes of this research. Eight informal sector activities were selected namely – petty trading, subsistence farming, commercial bike riding ("okada"), cattle rearing, fishing, tailoring, alluvial mining and quarrying.

More precisely, the first empirical paper used a random effect logit model to estimate households' WTP for health insurance for an improvement in coverage, choice of provider and a reduction in waiting time. The second empirical paper on the impact of corruption introduces two definitions of corruption – perceived and actual (free health care). The study used the mixed logit (MXL) model to estimate the impact of corruption on households' participation in health insurance. The final empirical paper on the other hand looked at ability to pay for health insurance. This paper is built on the assumption that simply perceiving need for health insurance is insufficient for someone to participate in it. Participation in health insurance is backed by the financial ability of the household to pay for health insurance. This study used two approaches: a univariate probit (naive) model and a recursive bivariate probit method (RBPM). We use data from discrete choice experiment to estimate ability to pay for health insurance.

Conditional on a set of covariates, the findings of the thesis suggest the following: first, that households are willing to pay for health insurance for an improvement in coverage, choice of provider (public and non-public) and a reduction in waiting time; second, that corruption generates substantial additional cost to households, hence the higher WTP to participate in schemes with evidence of corruption, more so, actual (free health care) corruption; and finally, that households do not have the financial capacity to pay for health insurance. Our result also shows that households that perceived NEED do not only have the ability to pay for it but are also not likely to participate in the scheme.

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Statement of Originality

I hereby certify that all of the work described within this thesis is the original work of the author. Any published (or unpublished) ideas and/or techniques from the work of others are fully acknowledged in accordance with the standard referencing practices.

This work has not been accepted for any previous degree.

This work has not yet been published.

Joseph Kamara

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Abbreviations

ACC	Anti – Corruption Commission
ATP	Ability to Pay
CA	Conjoint Analysis
CAR	Central Africa Republic
CIET	Community Information, Empowerment and Transparency International
CINAHL	Cumulative Index to Nursing and Allied Health Literature
CNL	Conditional Logit
CPI	Corruption Perception Index
CV	Compensating Variation
DCA	Discrete Choice Analysis
DCE	Discrete Choice Experiment
DfID	Department for International Development
EconLit	The American Economic Association Electronic Bibliography of Economic Literature
FCP	Financial Capacity to Pay
FFD	Fractional Factorial Design
FHC	Free Health Care
GAVI	Global Alliance for Vaccines and Immunization
GDP	Gross Domestic Product
GEV	Generalised Extreme Value
GP	General Practioners
HIV	Human Immunodeficiency Virus

IIA	Independence of Irrelevant Attributes
IID	Independent and Identically Distributed
IMR	Infant Mortality Rate
IUF	Indirect Utility Function
LCM	Latent Class Model
MABEL	Medicine in Australia: Balancing Employment and Life
MMR	Maternal Mortality Rate
MNL	Multinomial Logit
MRS	Marginal Rate of Substitution
MSL	Maximum Simulated Likelihood
MSLE	Maximum Simulated Likelihood Estimator
MXL	Mixed Logit
NHSSP	National Health Sector Support Project
NL	Nested Logit
OOP	Out of Pocket
PAC	Public Affairs Committee
PCI	Per Capita Income
PPP	Purchasing Power Parity
PubMed	The US Library of Medicine & the National Institute of Health Medical Library
QALY	Quality Adjusted Life Years
RBPM	Recursive Bivariate Probit Model
RE	Random Effect
RUM	Random Utility Maximization

RUT	Random Utility Theory
SAH	Self Assessed Health
SAS	Statistical Analysis System
SLL	Sierra Leonean Leones
SPSS	Statistical Package for the Social Science
SSA	Sub Sahara Africa
SSL	Statistics Sierra Leone
STD	Sexually Transmitted Disease
TI	Transparency International
UK	United Kingdom
US	United States
USD	United States Dollar
WHO	World Health Organisation
WTA	Willingness to Accept
WTP	Willingness to Pay

Chapter 1

Introduction

1.1 BACKGROUND

"The health situation in Sierra Leone is in a state of emergency with people dying every day because they do not have access to treatment. Asking people to pay for health care in such a context has devastating consequences, as many simply cannot afford the fees. For example, people wait to seek treatment until their health situation has become critical, or buy poor-quality medicine in the local market. Many do not even seek help at all". (Seso Gerard, Medicine San Frontiers advocacy advisor). [1]

The majority of households in Africa, when they are sick, do not have recourse to adequate mechanisms that will help them seek medical treatment. This is even worse for households in the informal sector that cannot access appropriate healthcare, particularly curative care, at the time of need. The majority of sub-Saharan Africa (SSA) health systems are dependent on out of pocket (OOP) spending. Unpredictable household health costs can impoverish even middle-income families that are not insured. A survey of 15 African countries showed that between 23 percent and 68 percent of uninsured households financed their OOP health expenses by borrowing and selling assets (Leive and Xu, 2008). In addition, evidence from surveys, which cover 89 percent of the world's population, suggest that annually about 150 million people suffer globally from financial catastrophe due to OOP health expenditures (Xu et al., 2007). Moreover, millions of people do not get the needed care because they do not have the financial resources to pay for care (ibid). These large OOP payments come in as both a burden and a barrier to accessing health care (Saksena et al., 2006).

The heavy reliance on OOP spending in health care is also not an uncommon situation in Sierra Leone, hence impeding access to health care. The high OOP expenditures make health care expensive in Sierra Leone, hence limiting frequent visits to the hospital. A large OOP expenditure in health care is known to reduce consumption expenditure on other goods and services and thus pushing households into poverty through catastrophic health expenditure.

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[1] Taken from the website www.doctorswithoutborders.org/news/article.cfm and accessed on 29th September 2012.

In countries wherein OOP health expenditures are high, health insurance is emerging in the literature as a preferred financing option to extend access to health care. Having a health insurance improves health care by improving access to health services that have a positive impact on health status (Escobar et al., 2010). A strong health care system balances prevention and intervention strategies, provides health care education for citizens, maintains an active workforce of health care providers and affords sufficient resources to confront illness. The purpose of health insurance therefore is three-fold: “increase access and use by making health services affordable, improve health status through increased access and use, and mitigate the financial consequences of ill health by distributing the costs of health care across all members of a risk pool” (Gideon and Diaz in Escobar et al., 2010).

The informal sector households are deprived from accessing health care due to the high OOP payments and other associated factors. The informal sector in Sierra Leone consists of all economic activities outside the formal institutional framework and cuts across both the rural and urban informal sectors respectively.[2] About two-thirds of the population in Sierra Leone lives in rural areas and are involved in informal sector activities (World Bank, 2013). The informal economy is deeply fragmented and diverse, with each group having its own needs though similar. The informal sector is grouped into the urban poor and the rural poor. The informal sector is characterized by low, irregular and insecure employment and lack of access to fair credit, which poses serious financial crisis (Ghosh and Mondal, 2011). They are exposed to a variety of diseases and health risks; poor access to safe drinking water and sanitation facilities; and overcrowding and poor housing hence making them vulnerable to waterborne and communicable diseases (ibid). They are dependent on risk coping mechanisms such as selling their assets to be able to pay for treatment fees, hence the reason for their frequent visits to “quack” doctors (ibid).[3]

Knowing the willingness and ability to pay for health insurance is crucial in ensuring the feasibility and sustainability of such schemes. A growing literature on the willingness-to-pay for health insurance suggests that the market for such schemes is large, even among the poor.

This thesis will look at the willingness and ability to pay for health insurance among informal sector workers in Sierra Leone.[4] This chapter therefore introduces the thesis.

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[2] See chapter 3 of thesis for a brief explanation of the informal sector in Sierra Leone
[3] “Quack doctors” are untrained and unqualified so – called doctors who are found mainly in remote and rural areas.
[4] Informal sector workers and informal sector households are used interchangeably through out this thesis

1.2 MOTIVATION AND JUSTIFICATION

Lack of access to health care and the high health expenditures in the form of high OOP expenditures have been raised in the literature as one of the primary causes of poverty and deprivation of rural households accessing health care in poor countries. This situation has the tendency to be slowed down through improved financing mechanisms like offering low-cost health insurance to low income households.

Sierra Leone has one of the worse health indicators in the world with about 53% of the population under the poverty rate of $1 a day, a GDP per capita of $374. Over two-third of the population lives in rural areas, a life expectancy at 46 years, an infant mortality rate (IMR) of 92 per 1000 births, an under five mortality rate of 156 per 1000 births, and a maternal mortality ratio (MMR) of 857 per 100 000 births (World Bank, 2013). About one-fourth of women do not receive post - natal care after delivery, about 46 percent of births are delivered outside a hospital/health centre, and 7 out of 10 women report having at least one problem in accessing health care (ibid). Health expenditure per capita is $96 as compared to $1048 for the world, and OOP expenditure as a percent of private expenditure is 61.3% compared to 34.6% for sub-Saharan Africa (ibid).

Health care is a serious problem in rural Sierra Leone wherein living standards are low and there is difficulty in accessing health care services due to the high OOP expenditures and absence of formal social protection systems like health insurance. Health insurance, it is argued will play an important role in accessing medical care and reducing the high OOP spending. Determining the willingness to pay (WTP) for health insurance will be crucial in ascertaining the feasibility of such schemes. A growing literature on WTP for health insurance suggests that the market for such schemes is large, even among the poor.

In addition, corruption is deeply rooted in the Sierra Leonean society and it is always the case that it wrecks viable institutions. Will corruption hinder household's decision to join a health insurance scheme? Will households afford the amount they suggested they are willing to pay, that is, do they have the capacity to pay for health insurance?

These and many other questions help in framing the design and focus of this thesis.

1.3 OBJECTIVE AND RESEARCH QUESTIONS

This primary objective of this thesis is to investigate and analyse 'Willingness and Ability to Pay for Health Insurance among Informal Sector Workers in Sierra Leone'. The four research questions used in this thesis therefore are listed below:

a. In which other healthcare studies has DCEs been used with reference to willingness to pay?
b. What is the willingness to pay for health insurance for informal sector workers in Sierra Leone?
c. What is the impact of corruption on informal sector households' willingness to participate in health insurance in Sierra Leone?
d. Are informal sector households' able to pay for health insurance in Sierra Leone?

The four research questions are presented hereafter and each one is briefly discussed.

1.3.1 First Research Question: In which other health Outcomes has DCEs been used with reference to willingness to pay?

The past three decades has witness the number of DCEs applied in health economics increased rapidly. What has happened down the years is that many researchers have concentrated on the state of practice of the DCE methodology and very few have looked at the classification of the application of the DCE methodology. Ryan and Gerard (2003), and De Bekker-Grob et al. (2012), have reported a detailed taxonomy of the application of DCEs in health economics. In these taxonomies, little or no emphasis was placed on the application of DCE in the area of WTP. This is where this paper comes in hand.

The paper '*Using Discrete Choice Experiment to elicit Willingness to Pay for Health Insurance: An Introduction and Systematic Review of the Literature'*, provides an exhaustive classification of the application of DCEs to health outcomes with specific reference to WTP. This work looks at the period 1990 to 2013.

1.3.2 Second Research Question: What is the willingness to pay for health insurance for informal sector workers in Sierra Leone?

The past four decades have witness a dramatic increase in the demand for health and health care coupled with the limited quantity of labour and capital resources, and this have led to an increasing interest in the efficient allocation of scarce resources through economic evaluation with a greater focus on health care choices (Ryan et al., 2010). Information about individuals' or households' preferences for health programmes and outcomes is needed (Viney et al., 2002). The allocation of scarce health care resources remains a contentious issue among practitioners.

There is an increasing interest in the economic evaluation of health care and this has resulted to its increased availability and acceptance as a tool for decision making in health and health care.

The WTP technique is the most popular economic evaluation technique to elicit preferences and is widely studied in the health economics literature. The two major methods widely used to determine WTP are the Discrete Choice Experiment (DCE) also known in the literature as Conjoint Analysis (CA) and Contingent Valuation methods. WTP is defined as the maximum amount that an individual or household is willing to pay for a good or service (DFID, 1997). The DCE technique, which is the focus of this paper, is the most widely used WTP technique over the past decades to elicit preferences in order to inform health care decisions. It is a stated preference and an attribute based hypothetical choice technique wherein more of one attribute is traded for less of the other (Lancsar and Louviere 2008, Luoviere and Lancsar 2009, Ryan and Gerard 2003).

In this paper *"Willingness to pay for health insurance among informal sector workers in Sierra Leone: A DCE Approach",* we estimate WTP for health insurance for households. We use the DCE method, which enables us to examine the degree to which each attribute influences the choice of the household, that is, to estimate the marginal rates of substitution (MRS) of the attributes, and allows us to obtain willingness to pay for an improvement in each attribute.

1.3.3 Third Research Question: What is the impact of corruption on households' participation in health insurance in Sierra Leone?

Most countries rely greatly on public systems for delivering basic health services. In addition, these health systems are under immense pressure to deliver effective and efficient services. However, it is often the case that the government cannot provide the necessary health services required either as a result of scarcity of resources or corruption (Mostert et al., 2012). It is documented that corruption in the health sector contributes immensely to the poor health of the population especially in developing countries. Over 80 percent of the world population is found in developing countries that are faced with increasing levels of corruption (ibid).

Lack of credibility and trust in fund managers has been highlighted as one of the reasons why people do not join health insurance schemes in developing countries especially in Africa (Escobar et al., 2010).

The paper, *"The impact of corruption on household's participation in health insurance: a case study of informal sector workers in Sierra Leone"*, will therefore investigate the impact of corruption on household's WTP for health insurance through (1) determining the relationship between household characteristics and actual and perceived corruption; (2) the fundamental differences between perceived and actual corruption; and (3) the magnitude of the impact of corruption on participation in health insurance. A discrete choice modelling process is used in the analysis.

1.3.4 Fourth Research Question: Are informal sector households' able to pay for health insurance in Sierra Leone?

Lack of access to health care is discussed in the literature as a major problem faced by people in developing countries especially poor households. To enhance access to health care, health insurance is emerging as the most preferred option for health financing in developing countries, moreso, where OOP is high (WHO, 2000). Health insurance is central to improvements in the health status of a country's population as it helps in accessing health care and reducing the high OOP. Estimating the WTP for health insurance is crucial in ascertaining the feasibility and sustainability of such schemes.

One of the key concerns in the literature with respect to WTP is that it does not show whether households can afford the amount they stated they are willing to pay. When WTP is backed by the financial capability, we say the individual or household has the ability to pay for that good/service in question.

The paper, *"Ability to pay for health insurance: a case study of informal sector workers in Sierra Leone"*, provides a detailed econometric analysis of ability to pay for health insurance. This paper is built on the premise that a household must perceive need first before participating in a health insurance scheme, that is, perceive need precede participation. It jointly estimates perceive need for health insurance and participation in health insurance. It jointly estimates also the impact of perceived need and the affordability threshold on participation in health insurance.

1.4 OUTLINE OF THESIS

The remainder of the thesis is organised as follows:

Chapter two introduces the DCE methodology and reviews the literature of the application of DCE to WTP for health outcomes including health insurance. This chapter looks extensively at WTP for health outcomes for the period 1990 - 2013.

Chapter three estimates WTP for health insurance among informal sector households in the Northern and Western region of Sierra Leone.

Chapter four estimates the impact of corruption on households' willingness to participate in health insurance.

Chapter five provides an empirical analysis of ability to pay for health insurance in Sierra Leone.

Chapter six summarises and concludes the work.

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Chapter 2: Using Discrete Choice Experiment to Elicit Willingness to Pay for Health Insurance: An Introduction and Systematic Review of the Literature

2.1 INTRODUCTION TO THE DISCRETE CHOICE EXPERIMENT METHOD

The focus of this chapter is to introduce the discrete choice experiment (DCE) methodology used to elicit preferences, and also to present a systematic literature review of the application of DCEs to elicit willingness to pay (WTP) for health outcomes including health insurance.

One of the main challenges facing poor countries, especially in Sub-Saharan Africa, is the lack of access to health care and the ineffectiveness of the health care systems. The majority of health care centres and hospitals are poorly equipped. Out of pocket (OOP) costs to finance basic health needs are high, hence the lack of access to health care in these countries. It has been suggested in the literature that the current health situation in poor countries can be improved by providing low cost health insurance schemes. It is believed that such schemes can help to improve access to health care by reducing OOP expenditure. There is therefore a need to measure the value households place on health and whether they would be willing to pay for health insurance, as well as how much.

WTP has been widely studied in the literature especially in the areas of marketing, environmental economics, transport economics, health and health care. Today, much of this interest is focused on the possibility of directly measuring individuals or households' WTP for non-marketed goods using survey methods. However, WTP is not as widely studied in health care as compared to the other fields. The two major methods widely used to determine WTP are Discrete Choice Experiment (DCE), otherwise known also as Conjoint Analysis (CA), and contingent valuation methods.[5] There has been a growing interest in DCE methodology and an increasing number of studies using it since its introduction in the 1980s. Compared to other fields, the methodology was used relatively late in health economics, but its application in the field has grown rapidly (de Bekker-Grob et al., 2012).

Following de Bekker-Grob et al. (2012), within the health sector DCEs have been used in a range of studies spanning patient or consumer experience factors, valuing health outcomes,

[5] A contingent valuation method is a survey method in which individuals/households are asked directly how much they are willing to pay for a good or service.

investigating trade-offs between health outcomes and patient or consumer experience factors, estimating utility weights within the Quality Adjusted Life Years (QALY) framework, job choices, developing priority setting frameworks, and health professionals' preferences.

A DCE is grounded in the assumption that any good/service is best described by its attributes (characteristics) and that the value of a good or service depends on the nature and level of these attributes (Ryan and Gerard, 2003). A DCE is an attribute-based hypothetical survey measure of value. Its premise is that a rational household will always choose the alternative that gives the highest level of expected utility. A DCE allows the researcher to model the policy objective into relevant attributes and to determine preferences for these different attributes.

As explained by Shackley and Ryan (1995), the DCE method has advantages over other methods: first, the DCE method explores how respondents trade between attributes; second, it identifies the researcher's strength of preference for different attributes of the good/service in question; third, it explores optimal ways of providing the good/service in question; and fourth, Adamowicz et al. (1998) argue that DCEs have greater validity and reliability due to their foundation in theory. However, Ryan and Watson (2009) maintain that there is little or no evidence to support the common assertion that DCE-based estimates are more valid than contingent valuation.

A few studies have conducted a literature review of DCEs in health economics. These include: Ryan and Gerard (2003), which looks at methodological issues in the application of DCEs to health from 1990–2000; Guttmann et al. (2009), which updates the work of Ryan and Gerard (2003) by including the period 2001–2007; Lagarde and Blaauw (2009), which looks at the application and contribution of DCEs to informing human resource policy interventions; and de Bekker-Grob et al. (2012), the most recently published systematic literature review of the application of DCEs to health care for the period 1990–2008.

In as much as some studies have reviewed the literature on the methodology of DCEs and its resultant choice data, little or no attention has been paid to the classification of specific areas DCEs have been applied to within the health sector. De Bekker-Grob et al. (2012) summarize areas where DCEs have been used. However, a detailed and up to date categorization is needed. While DCEs, health insurance and economic evaluation are very important issues in health economics; there is no study that reviews the literature of the application of DCEs to WTP for health outcomes including health insurance. The objective of this study therefore is to carry out a comprehensive and up to date classification of the application of DCEs to estimating WTP for health outcomes including health insurance, and to critically appraise studies regarding the various stages in the conduct of a DCE.

The remainder of the chapter is structured as follows: section 2 tries to answer the question what is a DCE and what is its theoretical basis? Section 3 explains the methodology of the chapter; section 4 presents the results in the form of a general overview of the application of DCEs to WTP and health insurance studies, the stages in conducting a DCE, validity issues and the inclusion of a cost attribute; section five concludes the chapter, drawing together the findings of the preceding sections.

2.1.1 Overview of the Discrete Choice Experiment Method

A DCE is a stated preference technique, which measures the relative importance that respondents place on the differing attributes of a good/service, and the extent to which trading takes place between these attributes (Ryan et al., 2010). Using the definition by Louviere et al. (2000), a DCE is an economic evaluation technique in which more of one attribute is traded for less of the other. It involves separating the good/service in question into distinct attributes and modelling satisfaction as a behavioural response, which comprises a random and a systematic component. The selected attributes are constant in each scenario, but the levels that describe each attribute vary systematically across scenarios, hence respondents choose the preferred option for each question. This rational decision making, according to Ben-Akiva and Lerman (1985), is based on a comparison of the levels of utility attained.

Singh et al. (1998) explain that the DCE method is based on three concepts: (i) each individual has a set of unique utility weightings relative to attribute levels; (ii) each good or service is a bundle of potential attributes; and (iii) combining the utility levels for different attributes provides an individual's overall relative utility weighting. However, for a DCE to be conducted, the following are required: the good or service must be made up of bundles of attributes; the most important attribute(s) of the good/service in question must have been identified; the attributes and levels should be actionable; respondents should be familiar with the concept and the overall objective of the study before they can rate the good/service.

According to Ryan and Gerard (2003), there are five main stages in the design of a DCE: attribute selection, assigning levels to chosen attributes, experimental design, data collection and data analysis.

Stage I: The Identification of Attributes

One of the critical issues in DCE design is the identification of relevant attributes, which can be quantitative (for instance cost, waiting time, risk etc.) or qualitative (e.g. health status domain, health care characteristics etc.), and their levels, describing the hypothetical scenarios under consideration. However, as explained by Mangham et al. (2008), the underlying validity of the study depends to a greater extent on the researcher's ability to correctly specify the relevant attributes. Of paramount importance in attribute selection is the objective of the study at hand, which in turn influences the type of attribute selected. A very important issue in the identification of attributes is judging what key attributes to include in one's work. Coast and Horrocks (2007) point out that there is no theoretical guide that explains how to select attributes. Ryan et al. (2010) supported this assertion by arguing that there are no hard and fast rules for identifying the number of attributes and the levels to assign to each. This therefore underlines that the entire process of attribute selection is subjective. Lancsar and Louviere (2008) and Bridges et al. (2011) posit that it is not feasible to include every attribute considered important to every respondent, but that attributes are to be selected based on their importance to the majority, and their relevance to policy making. Increasing the number of attributes has its associated problems; it leads to an increase in task complexity, fatigue and respondent burden. Hence, the number of attributes should always balance with these issues (Louviere et al., 2000; Hensher et al., 2005).

Stage II: The Identification of Attribute Levels

Once attributes have been selected, it is always necessary to assign levels to them. The levels should reflect the range of situations that respondents can expect to experience (Lancsar and Louviere, 2008). Ryan (1999) lists three key factors to be taken into consideration when assigning levels to attributes: they must be plausible (credible), actionable, and relevant to policy to exhibit trade between attributes.

The number of levels significantly influences the attributes, and as Louviere et al. (2000) explain, care must be taken in assigning levels for the following reasons: firstly, too many levels can result in respondents' fatigue as they have more choice questions to evaluate; secondly, the experimental design of the choice experiment increases in size and complexity with the number of attributes and attribute levels; finally, the selection of attribute levels has a large influence on the statistical power of the stated choice experiment. The number of attribute levels included in the experimental design affects the ability of the analyst to distinguish the non-linear relationships between the value of the attribute and its derived utility (Hensher et al., 2005).

Ratcliffe and Longworth (2002) investigated the issue of attribute effect in a study of alternative models of intrapartum care and found that respondents placed more emphasis on attributes with a higher number of levels.[6] This implies that attributes with more levels have a bigger impact on the model than attributes with fewer levels. This attribute effect can create bias in the result and hence the modelling. However, Curry (1997) explains that one way to minimize this problem is to assign the same number of levels to each attribute in the choice experiment.

Stage III: Experimental Design

The experimental design stage is all about efficiently combining attribute levels into profiles of alternatives and profiles of choice sets. There are four objectives in designing DCEs as explained by Louviere et al. (2000): first, identification of the choice experiment; second, ensuring that the statistical efficiency of the experiment is estimated precisely; third, cognitive complexity, i.e. ensuring that the experiment does not create excessive problems in understanding; and finally, market realism, which ensures that the choices (in both the experiment and the actual choices presented) are realistic. However, among the four design objectives outlined by Louviere et al. (2000), identification, as discussed by Louviere and Lancsar (2009), is crucial in design implementation because efficiency (how precisely the effects are estimated) can be improved by increasing the sample size, but identification cannot be changed once the design is constructed. Huber and Zwerina (1996) identify four principles for an efficient design of choice experiment: orthogonality (the most important design principle, the aim of which is to avoid multicollinearity between attributes, i.e. attribute levels should be independent of each other); minimal overlap (a design situation in which each attribute and its level appears only once in a choice task, and to ensure minimal overlap implies that one should ensure orthogonality is optimal); level balance (all attribute levels occur with equal frequency in the design experiment), and utility balance (the utility of each alternative within each choice set is equal). These properties are useful for understanding what makes a design optimal and efficient. Improving one of these properties and keeping the others constant will improve efficiency.

Factorial design is the most common method of designing a choice experiment. Factorial designs are divided into full factorial and fractional factorial. Full factorial design refers to a design method that includes all the possible choice situations (the combination of attributes and levels) and simultaneously estimates all possible effects (the main and interaction effects). Full factorial design is very important because it has a very appealing statistical property, i.e. it guarantees the independence of attribute effects (main effects only), hence allowing one to estimate and test all

[6] Attribute effect is the situation in which an increase in attribute levels, without altering the upper and lower levels, makes the attribute relatively more significant.

the possible main effects (Ryan et al., 2010) – an experiment with 5 attributes each with 3 levels results in $3^5 = 243$ factorials.

Although the full factorial design has attractive statistical features, it is not without its own shortfall, that is, it results in a large choice set that is impossible for a respondent to complete, hence making analysis complicated. Due to this shortfall, the design is in most cases reduced to a manageable size. Therefore, a fractional factorial design is often used and involves the selection of a portion of all possible profiles in which the properties of the full factorial design are maintained so that the effects of interest can be calculated as efficiently as possible. In the fractional factorial design, the interaction terms (two-way effects) are no longer orthogonal as compared to the full factorial design wherein both the attributes (main effects) and interactions (two-way effects) are orthogonal (ibid.). Within the fractional factorial type of design, there exist many different types of design including orthogonal arrays (a method in which all estimable effects are uncorrelated), D-efficiency (efficient design) and others that are pragmatically chosen (ibid.). The orthogonal array design involves minimizing the correlation between the attribute levels in the choice situations, and several forms exist including single profiles (binary choices), random pairing, pairing with a constant comparator, foldover, and random foldover. As too many overlaps will however reduce the information obtained through trade-offs between levels, it is advisable for designs to use choice sets that fulfil the demands of level balance, orthogonality and minimal overlap. Efficient designs are measures of design quality and they aim to be statistically as efficient as possible in terms of the predicted standard errors of the parameter estimates. The D-optimal design maximizes the information matrix (Huber and Zwerina, 1996) and helps to reduce the full factorial design to a manageable number/scenario.

The possibility of different fractional factorial designs depends on the effects that need to be estimated (main effects only or main effects with two interactions); how the profiles are to be presented to respondents, i.e. all profiles to all respondents, or a portion of profiles to a group of respondents; and what estimation method is to be used, i.e. a single or a multi-stage procedure. There are two major effects in designing a DCE – main and interaction effects. A main effect refers to the impact of the individual attributes, while an interaction effect refers to the impact of the dominant variable and the other factors in the model.

Stage IV: The Data Collection Stage

Data collection refers to the design of the sample frame, the sampling method to be used, the method to be use to recruit respondents, and methods for the administration of the survey. As long as the experimental design method has been agreed, a decision must be made regarding the method to be used for the administration of the survey. In developing an effective questionnaire for a DCE, the attributes and core concepts must be linked; the attributes should be piloted repeatedly to ensure plausibility and tradability, and clear directions must be given to respondents about the hypothetical nature of the task. DCE questionnaires should be designed to ensure orthogonality, minimal overlap, and level balance. There is no hard and fast rule as to the size of the sample to be used for a DCE. However, Hall et al. (2002) suggest that the sample size should range from 20–30 respondents per version. Notwithstanding this, Louviere et al. (2000) have obtained precise estimates using far lower sample sizes. In the DCE literature a minimum sample of 50 respondents is suggested for each particular subgroup of interest (Ryan et al., 2010; Mangham et al., 2008; Hensher et al., 2005). Johnson et al. (2013) on the other hand argue that sample sizes between 1,000–2,000 respondents would produce small confidence intervals, even if the experimental design were not particularly efficient. Hanson et al. (2005) go further to explain that the literature on Discrete Choice Analysis (DCA) offers limited guidance on what should be considered an appropriate sample size, and reveals that there is considerable variation in the number of individuals interviewed. However, they suggest that a minimum of 50 respondents is required to allow for an estimation of a reliable choice model consisting of main effects only.

On the issue of the number of choice questions to handle, Ryan and Hughes (1997) have shown that respondents can capably handle up to 13 DCE questions per interview. Kuhfeld (2010) argues that since orthogonal arrays are both balanced and orthogonal, they are 100% efficient and optimal, and Bliemer and Rose (2005) further explain that investing in more respondents leads to an orthogonal design being efficient. Although efficient designs have a lower standard error value and are more efficient than orthogonal designs, it is argued in the literature that increasing the sample size results in the orthogonal design having the same standard error values as efficient designs. As Bliemer and Rose (2005) put it:

> The D-error of the orthogonal design is approximately twice as high as the D-error of the D-efficient design. This means roughly that on average the standard error of the parameter estimates using the orthogonal design will be √2 times larger than the average standard error of the estimates using the D-efficient design. This in turn means that approximately twice as many observations using the orthogonal designs are required in order to obtain the same values of the standard error. (pp. 12)

<u>Stage V: The Data Analysis Stage</u>

The data analysis stage involves the estimation and interpretation of the findings of the experiment. The issue of the most promising discrete choice model to use in estimating DCEs has attracted growing debate in the literature. The nature of the choice problem and the experimental design determines the type of model to be estimated. The suitability of the estimation procedure depends on the presentation of the choice problem. Different choice models arise from different assumptions about the distributions and properties of the error components and about the variance/co-variance matrices of preference parameters. The distribution of the error term together with the type of choice modelled (binary or multinomial) will determine the specific econometric model form for the choice probabilities.

Binary probit and logit models are used in situations where respondents face a dichotomous choice (e.g. do you prefer service X: yes/no) or only two alternative choices (for instance preference for A or B). The probit model assumes a joint standard normal distribution of the unobserved utility components, while the logit model assumes a logistic distribution of the random component of the indirect utility function (IUF). The random effects (RE) model is used in situations where multiple observations are obtained from each respondent. The RE probit model is still the most popular dichotomous choice model in health economics (Guttmann et al., 2009).

When the choice option exceeds two, multinomial choice models are often used. The Multinomial Logit (MNL) is a model in which the respondent is simultaneously faced with three or more alternative choice options in which dummy coding of independent variables is quite common. There are three assumptions inherent in the MNL: the assumption of Independence and Irrelevant Attributes (IIA), i.e. choice probabilities will all change in proportion to the introduction of a new alternative or the deletion of an existing one; the error terms are Independently and Identically Distributed (IID) extreme value type 1 across observations; there is no taste heterogeneity, i.e. preferences are homogenous across respondents.

A key disadvantage of the MNL is expressing the direct consequence of the IID assumption as a proportionate shift, i.e. an increase in the probability of one alternative reduces the probabilities for all the other alternatives by the same margin.

Generalized Extreme Value (GEV) models like Nested Logit (NL), Mixed Logit (MXL) and Latent Class (LC) are choice models that are more behaviourally realistic. They relax the IIA property through the use of the general substitution pattern. The NL and MXL models are the most widely used GEV models and represent the most commonly used technique when standard testing procedures reject the IIA assumption. The NL partially relaxes the IIA assumption by grouping subsets of alternatives with similar characteristics that are present in other alternatives.[7]

In addition to the five stages discussed above, two other issues are important in estimating WTP using a DCE – validity, and the inclusion of a cost attribute in designing the experiment.

Validity Issues

Due to their hypothetical nature, DCEs have been criticized for failing to be related to (and ultimately predict) actual choices. The conclusions people draw from analyzing survey data are only acceptable to the degree to which they are determined valid. Validity is used to determine the extent to which research measures what it intended to measure and to approximate the truthfulness of the results (Skjoldborg et al., 2009; Telser and Zweifel, 2005). In quantitative research, testing for validity and reliability is a given. Reliability and validity issues are thought of in terms of systematic and random sources of error in measurement (ibid.).

The validity condition requires that there is no error in measurement. Validity could mean the extent to which the test measures what it purports to measure. There are many different types of validity: external, internal (theoretical and compensatory decision making), face, convergent, rationality and predictive validity, to name but a few (ibid.). External validity refers to the extent to which the results of a study can be generalized beyond the sample, i.e. you can apply your findings to other people and settings. Internal validity refers to the extent to which the independent variable can accurately be stated to produce the observed effect including the rigour in conducting the study and the extent to which the designers of a study have taken into account alternative explanations for any causal relationships they explore (i.e. the degree to which we can appropriately conclude that changes in X caused the changes in Y) (ibid.). Internal validity also involves testing whether coefficients of attributes are statistically significant and that the expected signs of estimated parameters are consistent with a priori expectations (theoretical validity), and whether respondents always choose according to the best level of a given attribute (compensatory decision making) (ibid.). Face validity basically measures the suitability of a given test instrument to measure the test it is designed to measure using common sense criteria. Convergent validity on the other hand tests the instrument with respect to WTP, standard gamble, and visual analogue etc.

A strong assumption in DCE is that of rationality (i.e., considering all available information, individuals make decisions on the basis of maximizing utility) and the willingness to trade

[7] For a detailed explanation of these models, see Hensher and Greene (2003), and Ryan et al. (2010).

between choices. The test of rationality (internal consistency) is about assessing whether respondents always opt for their preferred choice even when presented with differing options. In testing for rationality, a dominant choice set (which in most cases is an extra choice set) is often included in the questionnaire. Predictive validity measures the effectiveness of one set of test or research results as a predictor of the outcome of future experiments or tests.

The Inclusion of a Cost Attribute

In the estimation of WTP, cost needs to be included as one of the attributes to be used as a proxy for the marginal utility of income, hence the elicitation of WTP. The inclusion of a cost attribute or its proxy in a DCE depends to a large extent on the objective of the study in question. This implies that benefits are estimated in monetary terms, causing the DCE to be consistent with welfare economics (i.e. the potential Pareto improvement condition). The WTP also shows how respondents are willing to trade for improvements in other attributes of the good or service in question (Ryan and Gerard, 2003). The inclusion of a cost attribute also makes it possible to indirectly estimate marginal WTP, that is, the respondents' WTP for the attribute respectively. It is indirect because respondents are not asked directly how much they are willing to pay for a good or service as is often the case in contingent valuation studies, but respondents trade cost (or any monetary measure used) for other attributes.

The payment vehicles used in the cost attribute are user fees, tax, OOP expenditure, insurance premiums, user charges etc. As explained by Green et al. (1998), the term 'payment vehicle' basically comprises the form in which cost (payment) is specified in the survey, the conditions under which it is required and the link between response and potential payment. The choice of the payment vehicle has to be considered carefully, based on the type of health system in the location of the study. For example, in the UK, where the health care cost is borne by taxpayers in the form of taxation, using OOP expenditure as the payment vehicle will pose questions. It is therefore advisable to always consider both the type of health system in the country of study and the type of payment vehicle used. In developing countries where patients pay for health services at the point of delivery, there is a greater use of the cost attribute in studies dealing with such scenarios.

Another key issue to be taken into consideration in the evaluation of DCEs that include cost as an attribute is the issue of preferences for payment vehicles. To analyze this issue, Skjoldborg and Gyrd-Hansen (2003) have studied the effect of different payment vehicles (tax payment and user fee) with reference to the choice of hospitals and preferences for the Danish health care system. They conclude that a 1,000 kr. increase in tax payment for instance is not equivalent to a 1,000 kr.

OOP payment.[8] A final issue of concern is the duration of the payment: should it be weekly, bi-weekly, monthly, quarterly, half yearly or annually?

2.1.2 Theoretical Foundation of the DCE Methodology

The DCE has its theoretical foundation in random utility theory (RUT), which posits that a rational individual/household given a set of choice options will choose the alternative with the highest utility. The DCE is a choice based approach to consumer theory. However, Ryan et al. (2010) highlight three extensions to classic consumer theory that are of importance to DCE analysis. First, consumer theory assumes the goods are homogenous and that utility is a function of quantities; discrete choice theory however, based on Lancaster's (1966) theory, assumes that the attributes of a good determine its utility. Second, the discrete choice theory assumes choice is made amongst a finite and mutually exclusive set of alternatives (the household chooses only one alternative at any point in time), rather than households selecting an alternative within an infinitely divisible space, as is the case in the classic theory of consumer choice. Finally, a household's choice behaviour in discrete choice theory is rather probabilistic (random), rather than deterministic as in classic consumer choice theory.

The idea behind RUT in discrete choice theory is that part of a household's utility for an alternative is latent (hidden). RUT posits that the utility (U) for household *i*, conditional on choice *j*, can be decomposed into a systematic component V_{ij} and a random component ε_{ij}:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad j = 1\ldots\ldots\ldots\ldots J \qquad (2.1)$$

where U_{ij} is the utility the *i*th household expects to get from choosing health insurance *j*.

However, the systematic component V_{ij} is a vector of the attributes of the good/service X_{ij} as viewed by the household and the characteristics of the household Z_i in question. The explained component therefore becomes:

$$V_{ij} = X_{ij}\beta + Z_i\gamma \qquad j = 1\ldots\ldots\ldots\ldots\ldots\ldots J \qquad (2.2)$$

X_{ij} is the vector of attributes of health insurance *j* as viewed by household *i*; Z_i is a vector of characteristics of household *i*; β and γ are vectors of coefficients to be estimated.

From equation (2.1) above, the unexplained component captures the unobserved variation in the characteristics of different options. The random component may however be due to errors in

[8] The Danish Krone (kr.) is the local currency used in Denmark.

measurement or specification, unobservable attributes, preference variation, or household variability. Since the random component is unobservable in choice, a household's choice is therefore probabilistic rather than deterministic. The basic assumption underlying equations (2.1) and (2.2) is that household j will choose say alternative i if and only if that alternative maximizes their utility amongst all j alternatives in the choice set.

If the error term (ε_i) in equation (2.1) above is jointly distributed, the theory states that the probability of maximizing utility by choosing the alternative is thus:

$$Prob(Y_i = j| j,k) = Prob(U_{ij} > U_{ik})$$
$$Prob\ (V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}) \qquad \forall\ j \neq k;\ k = 1, 2\ldots\ldots\ldots J \qquad \text{or}$$
$$Prob\ (V_{ij} - V_{ik}) > (\varepsilon_{ij} - \varepsilon_{ik}) \tag{2.3}$$

Where Y_i is a random variable denoting household i's choice.

Equation (2.3) is developed from the basic assumption that household i will choose alternative j if and only if alternative j maximizes their utility given alternatives j and k in the choice set.

It is not possible to estimate the term $(\varepsilon_{ij} - \varepsilon_{ik})$, thus researchers cannot say exactly if $(V_{ij} - V_{ik})$ is actually more than $(\varepsilon_{ij} - \varepsilon_{ik})$, but they can predict the probability of occurrence that household i will choose alternative j. From equation (2.3) above, the joint probability distribution for the non-explainable random component is chosen based on what is known about the unobserved factors and dictates how DCE preferences are modeled.

Estimable choice models are derived by assuming a distribution for the random component in equations (2.1) and (2.3) and the nature of the choice being modelled. The type of model to be used depends on the assumption of the error term and the number of alternatives presented in the choice experiment. As put forward by Ryan et al. (2010), if the choice faced by the individual is dichotomous, a binary choice model is appropriate. The most widely used binary choice models in the literature are the logit and probit models. On the other hand, a lot of studies in recent times have focused on more than two alternatives being presented in a choice situation. For such situations, multinomial and conditional logit models are popularly used. The multinomial and conditional logit models assume that the errors are independently and identically distributed (IID) with a Gumbel distribution. The choice probabilities can be expressed as shown below:

$$Prob(Y_i = j | J) = \frac{e^{V_{ij}}}{\sum_{j=1}^{k} e^{V_{ij}}} \tag{2.4}$$

The main difference between the multinomial logit (MNL) and the conditional logit (CNL) is that the MNL model depends on the differences in coefficients across alternatives. Rather than focusing on the household as the unit of analysis, the CNL model focuses on the set of alternatives for each individual, and the explanatory variables are characteristics of those alternatives. Therefore, the CNL model depends on the differences in the value of the characteristics across alternatives.

It is possible to determine the relative importance of each attribute by estimating the marginal rate of substitution (MRS), which is the maximum amount of an attribute a consumer is willing to sacrifice to obtain one more unit of the other attribute in question. From equation (2.2), our MRS is the ratio of the derivatives of the indirect utility function with respect to two attributes (say 1 and 2) is written thus:

$$MRS_{12} = \frac{dV/dX_{1i}}{dV/dX_{2i}} = \frac{\beta_1}{\beta_2} \tag{2.5}$$

When a monetary attribute is added as one of the attributes, the MRS indicates the household's WTP. If X_2 is say the cost of the health insurance scheme, then equation (2.5) becomes

$$WTP_i = \frac{dV/dX_{1i}}{dV/d_{cost_i}} = \frac{\beta X_{1i}}{\beta_{cost_i}} \tag{2.6}$$

Equation (2.6) is our WTP, which measures the change in the qualitative attribute. From equations (2.1) to (2.6), the βs (part-worths) are used to establish a number of issues. First, their statistical significance will indicate the importance of the attribute estimated by the respondent; second, upon its significance, the size of the coefficient directly correlates with the size of the impact the attribute has on the overall utility; third, the ratio of the coefficients shows the trade-off between attributes; and fourth, utility scores can be estimated for different combinations of attributes.

2.2 LITERATURE REVIEW OF THE DISCRETE CHOICE EXPERIMENT METHOD APPLIED TO HEALTH ECONOMICS

A systematic review of the literature has been conducted with the aim of identifying and evaluating published English Language studies using the application of DCEs/CAs in health economics literature from January 1990 to December 2013. However, this study focuses primarily on the application of DCEs to WTP and health insurance in health economics.

The bibliographic databases used were the US National Library of Medicine and the National Institutes of Health's Medical Library (PubMed); the American Economic Association electronic bibliography of Economic Literature (EconLit); the Cumulative Index to Nursing and Allied Health Literature (CINAHL); JSTOR, Scopus and Google Scholar.

The key terms used in the search were "discrete choice experiment", "conjoint analysis", "health insurance", "willingness to pay", and "health care". Added to the above, the study has made use of the same text terms applied by Ryan and Gerard (2003). The terms include "conjoint study", "part-worth utilities", "pairwise choices", "discrete choice conjoint experiments", "stated preference". Each of the key terms were searched separately, and then combined using the Boolean search technique.

In classifying the studies retrieved, the following inclusion and exclusion criteria were used: Studies were included if they were applied to WTP using DCE/CA; to health insurance using DCE/CA; to health care using DCE/CA; if they had cost as one of the attributes; if the study calculated WTP as one of its findings; if it was experimental and grounded in Random Utility Theory (RUT); if the study was a choice-base response data exercise; and if they dealt with the stages in conducting a DCE.[9] Issues relating to the criteria to be used regarding methodological quality took centre stage when conducting systematic literature reviews. These have however been addressed by looking at the stages involved in conducting DCEs as proposed by Ryan and Gerard (2003). However, studies were excluded if they were not in English language, not a DCE/CA study, cost was not included as one of the attributes, they were not related to health, they were presentations, editorial, or methodological reviews.

The search methodology resulted in 2,235 possible references and citations. After a thorough and careful combination of key words in the search, a total of 353 articles were selected. However, after a thorough reading of the articles and taking into consideration of the inclusion and exclusion criteria, 199 articles were included for review in this study. Appendix 2A shows the

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[9] Cost here refers to financial cost and also includes price, OOP expenditure etc.

complete list of articles, grouped by area of application. The main areas the studies were applied to, as listed in this work, were as follows: Willingness to Pay (28); Health Insurance (1); Health States/Economic Evaluation (22); Patient/Physician Relationship/Preferences (25); Health Care (14); Diagnostic Services (14); Cancer (12); HIV/STDs (7); Pharmaceutical (6); Reproductive Health (11); Surgical Health Outcome (6); Other Health Outcomes (15);[10] Human Resources (28) and Others (10).[11]

Table 2.1 below summarizes the background information on the articles used in this review for the period 1990–2013. The background information includes the number of articles per year and the country within the period under review.

Table 2.1: Background Information of DCEs[1]

Year	Baseline 1990–2000 N = 14(%)	2001-2010 N = 106(%)	2011-2013 N = 79(%)	Country	Baseline 1990–2000 N = 14(%)	2001–2010 N = 114(%)	2011–2013 N = 97(%)
1990–2000	14(100)			UK	7(50.0)	27(23.7)	12(12.4)
2001		2(1.9)		Australia	1(7.1)	13(11.4)	7(7.2)
2002		10(9.4)		Germany	0(0)	5(4.4)	6(6.2)
2003		4(3.8)		Canada	1(7.1)	5(4.4)	11(11.3)
2004		12(11.3)		France	0(0)	3(2.6)	3(3.1)
2005		11(10.4)		Netherlands	0(0)	8(7.0)	4(4.1)
2006		12(11.3)		USA	4(28.6)	15(13.2)	7(7.2)
2007		13(12.3)		Denmark	0(0)	6(5.3)	6(6.2)
2008		12(11.3)		Spain	0(0)	5(4.4)	2(2.1)
2009		13(12.3)		Europe[2]	0(0)	10(8.8)	12(12.4)
2010		17(16.0)		S. America	0(0)	0(0)	5(5.2)
2011			15(19.0)	Africa	0(0)	11(9.7)	13(13.4)
2012			34(43.0)	Asia	1(7.1)	6(5.3)	9(9.3)
2013			30(38.0)				

1. The numbers in brackets are percentages
2. Europe refers to other European countries apart from the following: UK, Germany, France, Netherlands, Denmark and Spain.

Table 2.1 above shows that a little over half (53.3%) of the studies reviewed were conducted during the period 2001–2010. During this period, the popularity of the DCE methodology was gaining momentum in health economics. However, 2001 and 2003 were the periods with the least number of studies; in 2001 only two studies were conducted whereas in 2003 only four studies were reported. On average, about 10 studies per year were conducted within the period 2001–

[10] Other Health Outcomes refers to articles dealing with health outcomes outside those listed above and includes issues like stroke, skin, dental care, asthma, lungs etc.
[11] Others refer to articles dealing with other health related issues outside the objectives listed above. An example of such an article is demand for environmental policies to improve health.

2010. The trend improved in the new decade, i.e. 2011–2013, as about 26 studies per year were conducted.

Within the first period, 1990–2000, 50% of the studies were conducted in the UK while a little over a quarter were conducted in the US. The UK and US alone covered about 75% of the studies conducted within the period 1990–2000. Overall, from 1990–2013, the picture is clearer as 116 (about 52%) of the 199 studies were carried out in Europe, with the UK alone accounting for 40% of the total. Classifying the studies by continents gives the following results: North America (Canada and US) has 43 (about 19%) of the studies to its credit, 60% of these being from the US; 21 (9.3%) of the studies are from Australia, with about 62% being carried out between 2001–2010; 24 (10.7%) are from Africa, with 54% of these studies being carried out between 2011–2013; 16 (7.1%) are from Asia, and 5 (2.2%) from South America. It is interesting to note that during the period 1990–2000, no studies were carried out in Africa, but from 2001–2013, the number increased greatly to 24. The majority of these studies focused on human resource issues. Developing countries (Africa, Asia and South America) produced 45 (about 20%) of the total studies, about the same as the UK. The reasons for the low number of DCE studies regarding health insurance and WTP in developing countries can be attributed to the following challenges faced when conducting a DCE: (1) working in different cultural or language settings; (2) administering a questionnaire to a population with a high illiteracy rate; and (3) the difficulty in accessing relevant information on specific health concerns and individuals'/households' concerns being poorly sounded out (Mangham et al., 2008).

2.2.1 A General Overview of the Application of DCE to WTP

The classification of the studies was based on their objectives. The key classification areas were economic evaluation, health outcomes and others. The first two were subdivided into specific objectives to get a clearer picture of the studies under review as shown in Table 2.2 below. As WTP is one of the primary objectives of the studies under review, it was excluded from the economic evaluation studies, hence subdividing economic evaluation into studies with WTP as their main objective and economic evaluation and health outcomes as their other objectives. Health outcomes, the mainstay of the studies, were subdivided further into specific health concerns as shown in Table 2.2 below. Others include studies that do not fall into either the economic evaluation or health outcome objectives but are related to health, for instance the demand for environmental health, valuation of mortality, willingness to donate body parts etc.

Table 2.2 below shows the number of studies (articles) based on their objectives.

Table 2.2: Areas of Application of DCEs

Study Objective	Number of Articles	%
Willingness to Pay	28	14.1
Economic Evaluation & Health Outcomes	22	11.1
Patient/Physician relationship/preferences	25	12.6
Health Care	14	7.0
Diagnostic Services	14	7.0
Cancer	12	6.0
HIV/STDs	7	3.5
Pharmaceutical	6	3.0
Health Insurance	1	0.5
Reproductive Health	11	5.5
Surgical Health Outcome	6	3.0
Other Health Outcomes	15	7.5
Others	10	5.0
Human Resources	28	14.1

The objectives of WTP and human resources account for the joint highest number of studies carried out (14.1%).[12] However, if combined, the objectives of WTP, patient/physician relationships/preferences and human resources, account for about 40% of the studies. As will be observed in the subsequent sections of this chapter, the cost attribute is used in all the studies, hence calculating WTP. However, although WTP was calculated in almost all the studies it was not the objective in the majority of them. The studies that had WTP as their objective estimated WTP for the overall sample as well as for predefined subgroups. Only one study (Vroomen and Zweifel, 2011) looked at health insurance as its objective. This looked at preferences for health insurance and health status and whether it matters if you are Dutch or German. The two major research questions were first, do individuals with a chronic condition (as an indicator of permanent health status) value attributes of health insurance differently from others, and second, do these valuations depend on the country? For the first question, it was found out that patients with chronic conditions value health insurance attributes differently because of their status, and that their valuations depend on their location (country).

[12] Note that in as much as WTP is calculated in all the studies, it is still not the primary objective for most of the studies. That is why the studies with WTP as their objective are fewer.

2.2.2 A Review of the Stages in Conducting a DCE in the Literature

As explained in section 2.1.1, there are five key stages in conducting a DCE. Stage one involves choosing the attributes that are relevant to the policy objective at hand; stage two involves assigning levels that are actionable and plausible for the chosen attributes; the third stage is the experimental design stage, which forms the foundation for a successful DCE design; stage four involves the collection of data; and the fifth stage is the analysis of the data collected.

2.2.2.1 The Identification of Attributes and Levels in the Literature

The identification of attributes and assigning levels to them are the first stages in the design of a DCE relevant to the stated research question (Ryan and Gerard, 2003). The identification of attributes is necessary for a successful DCE, and to correctly specify the relevant attributes is important for the validity of the study (Mangham et al., 2008).

Within the health sector, identifying attributes can be difficult and complex, hence requiring a thorough understanding of the population in question. Reviewing published and grey literature, focus group discussions, semi-structured interviews and surveys of key stakeholders are some of the methods used to identify attributes.

The objective of a study influences to a large extent the kind of attributes selected for that study. For instance, the objective to determine WTP requires that a cost attribute is selected to ensure WTP is calculated later in the study. Table 2.3 below shows the attributes covered by the studies in this review.

Table 2.3: Attributes Covered in the Literature

	1990–2000	2001–2010	2011–2013
Attributes Covered[1]			
Monetary Measure	14	106	79
Time	10	38	25
Risk	0	11	14
Health Status Domain	5	35	28
Health Care	4	25	14
Location	3	16	9
Sensitivity	1	1	5
Severity	0	8	22
Chance/Likelihood/Probability/Possibility	7	17	17
Frequency	1	14	16
Others, Including Staff Welfare	8	55	47
Number of Attributes Covered			
2–3	1 (7.1)	7 (6.6)	5 (6.3)
4–5	6 (42.9)	28 (26.4)	31 (39.2)
6	5 (35.7)	41 (38.7)	18 (22.9)
7–9	1 (7.1)	20 (18.9)	23 (29.1)
10	0 (0)	5 (4.7)	0 (0)
More than 10	1 (7.1)	5 (4.7)	2 (2.5)
Total	**N = 14 (%)**	**N = 106 (%)**	**N = 79 (%)**

1. The total number of attributes covered far exceeds 398 (a minimum of 2 attributes per study) because most studies dealt with more than two attributes.

From Table 2.3 above, one can see that the monetary measure attribute was the most widely used attribute in the studies reviewed. All the studies used the monetary measure as an attribute. The reason is quite obvious because the objective of this work is to review DCEs with respect to WTP and health insurance/health care. One major criterion for estimating WTP using the DCE is to include a monetary measure (cost) attribute, hence calculating the WTP. The attributes time (which includes waiting time for a test or an appointment to see a doctor), health status domain and others (including staff welfare) were the three most widely used attributes in most of the studies reviewed. About one fifth of the attributes covered in the studies reviewed were either time or health status domain related. Amongst the attributes used in the studies reviewed, sensitivity was the least widely used.

As explained earlier, a very important issue in the identification of attributes is the number of attributes to include in a DCE. As there is no generally accepted number of attributes to use in a DCE study, Table 2.3 also shows the number of attributes used in the studies reviewed.

As shown in Table 2.3, about two thirds of the studies reviewed use on average 4–6 attributes. One possible explanation for this as given by Deshazo and Fermo (2002) is that the smaller the number of attributes covered, the greater the chances of respondents being able to consider all attributes when making their choice. Therefore, the greater the number of attributes, the more chances there are of facing difficulty in completing the DCE. Table 2.3 supports this statement as about 29% of the total number of studies used seven or more attributes, while the remaining 71% used less than 7 attributes. About 87% of the total studies reviewed use 4–9 attributes. This supports general claims in the literature that using too small a number of attributes gives respondents less opportunity to have a clear view of the good/service in question. However, using too many attributes increases the DCE complexity and respondents' burden in comprehending the experiment.

Lancsar and Louviere (2008) argue that the levels should mirror situations that respondents expect to experience in the experiment. To increase the accuracy of estimates, the attributes and levels must be realistic, mutually exclusive, comprehensive, meaningful and quantifiable. In the majority of the studies reviewed, between 2–4 attribute levels were used. An increase in the number of attribute levels without influencing the upper and lower levels would cause that attribute to have a bigger impact on the model than an attribute with fewer levels. A wide range of levels is often used to prevent respondents ignoring attributes because of a small difference in levels. The issue of level range is also particularly important for experiments that have a price (monetary measure) attribute, especially when used to estimate the MRS of other attributes. Skjoldborg and Gyrd-Hansen (2003) have found that changing the price vector changes the parameter estimates and MRS, which in turn compromises the experimental design and hence introduces bias into the experiment.

2.2.2.2 Experimental Design and Construction of Choice Sets in the Literature

Experimental design is all about efficiently combining attribute levels into profiles of alternatives and profiles of choice sets. An experimental design is developed in two phases: first, obtaining the optimal combination of attribute and attribute levels to be included in the experiment, and second, combining those profiles into choice sets.

There are several methods used to create choice sets but the most widely used are orthogonal arrays, D-efficiency, block design and other methods that are pragmatically chosen. The notable ways to create designs include computer software packages like SAS, SPSS, SPEED, and SAWTOOTH, catalogues;[13] websites[14] and experts.[15]

As explained earlier, the experimental design stage is considered the most important and crucial stage in the design of a DCE (Lancsar and Louviere, 2008; Ryan et al., 2010). This stage determines the kind of econometric method to be used. The subsequent tables show the experimental design issues in a DCE raised by the articles reviewed.

The majority of the studies reviewed included a neither or opt out option in their DCE questions to prevent respondents from being forced into choosing a good/service. According to Lancsar and Louviere (2008), the exclusion of an opt out option could be a violation of the underlying welfare measure of the economic experiment as it makes it impossible to estimate the value of doing nothing, which may be chosen in practice.

Table 2.4 below shows the choice sets and the methods used to create them.

Table 2.4: Attributes and Choices

Item	Category	1990–2000	2001–2010	2011–2013
Number of Choice Sets		**N = 14 (%)**	**N = 106 (%)**	**N = 79 (%)**
	≤ 8 choice sets	2 (14.3)	28 (26.42)	13 (16.46)
	9–16 choice sets	7(50)	56(53.83)	45(56.96)
	16 choice sets	4(28.6)	15(14.15)	13(16.46)
	Not clearly stated	1(7.1)	7(6.60)	8(10.13)
Methods to Create Choice Sets		**N = 14(%)**	**N = 106 (%)**	**N = 79 (%)**
	Orthogonal Arrays	8 (57.1)	66 (62.26)	27 (34.18)
	• Single Profiles	2 (25)	9 (13.64)	5 (18.52)
	• Random Pairing	2 (25)	30 (45.45)	10 (37.04)
	• Pairing with constant comparator	3 (37.5)	23 (34.85)	4 (14.81)
	• Fold over – Random Pairing	1 (12.5)	1 (1.52)	2 (7.41)
	• Fold over	0 (0)	3 (4.55)	6 (22.22)
	D–Efficiency	0 (0)	7 (6.60)	15 (18.99)
	Block Design	2 (14.3)	7 (6.60)	10 (12.66)
	Others*	0 (0)	11 (10.38)	12 (15.19)
	Not Clearly Reported	4 (28.6)	15 (14.15)	15 (18.99)

* Includes Shifting, D–Optimal and Orthogonal Mixed Effect Designs

[13] An example of such a catalogue is Hahn and Shapiro (1966)
[14] An example of such a website is http://www.research.att.com/~njas/oadir/
[15] Examples of experts include John Rose and Deborah J. Street and Leonie Burgess

From Table 2.4 above, one can see that about 54% (108) of the studies reviewed used choice sets ranging from 9–16. There is still an ongoing debate on the exact number of choice sets to include in a DCE. De Bekker–Grob et al. (2012) for instance, explain that the appropriate number of choice sets to use is context specific. However, Ryan and Gerard (2003) are specific, suggesting that the number of choice sets most commonly used ranges from 2–16. This is supported in this review as about 76% of the studies reviewed used 16 choice sets or less. The common reason advanced is the cognitive capacity of respondents. However, in precise and specific terms, Louviere et al. (2000) and Froberg and Kane (1989) suggest that choice sets should be defined over no more than nine attributes because "research has shown that human beings can process simultaneously only five to nine pieces of information" (p. 346). In addition, Hensher et al. (2005) and Louviere et al. (2000) confirm that studies have shown that there exists an inverse relationship between the number of choice sets and its impact on the response/completion rate.

Taking a look at the methods to create choice sets, it is evident from Table 2.4 that orthogonal array is the most widely used method as about half of the studies used it. Among the orthogonal arrays, random pairing (about 42% of orthogonal arrays) and pairing with a constant comparator (about one quarter of orthogonal arrays) are the most widely used methods. However, pairing with a constant comparator is used to test the internal consistency (rationality) of the questionnaire. Table 2.5 below shows the type, plan and source of the design for the various studies reviewed.

Table 2.5: Design Type, Plan and Source

Item	Category	1990–2000	2001–2010	2011–2013
Design Type		**N = 14 (%)**	**N = 106 (%)**	**N = 79 (%)**
	Fractional	9 (64.3)	72 (67.92)	41 (51.90)
	Full	1 (7.1)	3 (2.83)	4 (5.06)
	Not Reported	4 (28.6)	31 (29.25)	34 (43.04)
Design Plan[1]		**N = 14 (%)**	**N = 107 (%)**	**N = 80 (%)**
	Main Effects Only	7 (50)	48 (44.86)	22 (27.50)
	Main Effects (Two way Interaction)	0 (0)	9 (8.41)	8 (10.00)
	Not Reported	7 (50)	50 (46.73)	50 (62.50)
Design Source		**N = 14 (%)**	**N = 106 (%)**	**N = 79 (%)**
	Software Package	8 (57.1)	52 (49.06)	49 (62.96)
	✓ SPEED	3 (37.5)	13 (25.00)	1 (2.04)
	✓ SPSS	2 (25)	16 (30.77)	4 (8.16)
	✓ SAS	0 (0)	13 (25.00)	25 (51.02)
	✓ SAWTOOTH	1 (12.5)	7 (13.46)	13 (26.53)
	✓ NGENE	0 (0)	0 (0)	4 (8.16)
	✓ STATA	0 (0)	0 (0)	1 (2.04)
	✓ Others[2]	2 (25)	2 (3.85)	0 (0)
	✓ No further details	0 (0)	1 (1.92)	1 (2.04)
	Catalogue	0 (0)	3 (2.83)	4 (5.06)
	Website	0 (0)	2 (1.89)	2 (2.53)
	Expert	0 (0)	11 (10.38)	5 (6.33)
	Not clearly reported	6 (42.9)	38 (35.85)	19 (24.05)

1. Some studies used both effects

2. Includes other software apart from those listed

It is evident from Table 2.5 that fractional factorial design is the most widely used type of design for choice experiments. About 61% of the studies reviewed used this method whereas only about 4% of the studies made use of the full factorial design method. The reason for this is quite obvious as the full factorial design method leads to a higher number of choice sets which become difficult for respondents to comprehend. The fractional factorial design presents respondents with fewer choice sets, which they can understand better.

On the issue of design plan, about 38% of the studies reviewed used the main effects only as compared to about 8% that used the main effects with two-way interactions. The main effects only design plan is used mostly when the focus is to calculate WTP, hence its more frequent use in the studies reviewed.

Looking at the sources for designing the experiment, one can observe from Table 2.5 that about 55% of the studies used the software package. The expert design was the second most widely used source of DCE design. SAS, SPSS and SAWTOOTH (35%, 20% and 19% respectively) were the most commonly used software packages in the studies reviewed.

Tables 2.4 and 2.5 show that orthogonal main effect designs are still the most commonly used design method in DCEs. The reason for their wide usage is the typical advantage they have of being smaller than the other designs.

2.2.2.3 Literature on Data Collection for DCE

The design of the sample frame and the decision regarding which method to use to sample the population, recruit respondents and administer the survey, all form the basis of data collection. DCE questionnaires should be designed to ensure orthogonality, minimal overlap and level balance. A survey should include the key instructions respondents need to know in answering the questionnaire spanning from contextual information, demographics, socio-economic and demographic data pertaining to choice. The issue of the sample size to use in a DCE is inconclusive in the literature. However, some studies (Bishop et al. 2004, Herbild et al. 2009) have shown that sample sizes between 300–400 respondents are sufficient for reliable statistical analysis.

In the literature there are three main methods for administering surveys: self-complete questionnaire, interviewer-administered, and computerised interview. Table 2.6 below presents the methods of administering surveys and the available response rates in the studies under review.

Table 2.6: Methods of Administering Surveys and Response Rates

Item	Category	1990–2000	2001–2010	2011–2013
Administration of Survey[1]		**N = 15 (%)**	**N = 109 (%)**	**N = 80 (%)**
	Self-complete questionnaire	9 (60)	49 (44.95)	34 (42.50)
	Interviewer-Administered	2 (13.3)	41 (37.61)	13 (16.25)
	Computerised Interview	2 (13.3)	6 (5.50)	18 (22.50)
	Not Reported	2 (13.3)	13 (11.93)	15 (18.75)
Response Rate		**N = 14**	**N = 106**	**N = 79**
	< 50%	2 (14.3)	12 (11.32)	11 (13.92)
	51%–75%	5 (35.7)	27 (25.47)	17 (21.52)
	76%–100%	4 (28.6)	54 (50.94)	30 (37.97)
	Not Reported	3 (21.4)	13 (12.26)	21 (26.58)

1. Some studies used more than one method for administering a survey.

From table 2.6 above, one can see that the self-complete questionnaire method for administering a survey accounts for about 45% of the methods used in the studies. This method is common because of the ease it gives the respondent to complete the questionnaire; it minimizes human error in coding, data entry and management, and data collection is faster than the other methods. However, this method is common with a sample with a high level of literacy. About 27% of the studies under review used the interviewer-administered method. About 44% of the studies had excellent (76%–100%) response rates, while only about 12.5% had very poor response rates (less than 50%). This shows that majority of the DCE studies had very good response rates.

2.2.2.4 Data Analysis and Model Estimation Procedures used in the Literature Review

This section looks at the various econometric methods used in the studies under review, and the reasons for using them. When respondents are faced with two options or alternatives, the logit, probit, RE probit and RE logit are the most widely used econometric methods. However, for three or more alternatives, the MNL, CNL and MXL models are the most widely used methods.

Table 2.7 below shows the estimation methods used in the studies under review.

Table 2.7: Estimation Methods Used

Estimation Method	1990–2000	2001–2010	2011–2013
	N = 14 (%)	N = 106 (%)	N = 79 (%)
Probit	2 (14.4)	3 (2.83)	2 (2.53)
Random Effect (RE) Probit	8 (57.2)	32 (30.19)	2 (2.53)
Logit	0 (0)	13 (12.26)	4 (5.06)
Random Effect (RE) Logit	0 (0)	3 (2.83)	3 (3.80)
Multinomial Logit	1 (7.1)	5 (4.72)	8 (10.13)
Mixed Logit	0 (0)	7 (6.60)	16 (20.25)
Conditional Logit	1 (7.1)	13 (12.26)	11 (13.92)
Nested Logit	0 (0)	2 (1.89)	2 (2.53)
Other Methods[1]	1 (7.1)	12 (11.32)	11 (13.92)
Two or more Methods	1 (7.1)	9 (8.49)	15 (18.99)
Not Stated	0 (0)	7 (6.60)	5 (6.33)

1. This includes RPL, WLS, OLS, MLE, and ANOVA etc.

As shown in Table 2.7, the RE probit method seems to be the most widely used method, accounting for about one fifth of the estimation methods used in the studies under review. All the family of probit (probit and RE probit) models account for about one quarter of the estimation methods used. However, the logit family of model estimation methods were used in about 45% of the studies in this review. Within the logit family, the CNL and MXL models were the most widely used estimation methods and they account for about 53% of the logit models used. About 36% of the studies used binary choice only as their estimation method. Multinomial choice methods (MNL, CNL, MXL, NL), were used by about 33% of the studies. During the period 1990–2000, about 71% of the studies reviewed used binary choice methods only whereas multinomial methods were used in 14%. However, the use of multinomial choice methods has increased greatly in recent years. From 2011–2013, we see that about 49% of the studies reviewed used the multinomial choice method while 14% used the binary choice method. This shows that the multinomial choice method has been gaining popularity.

2.2.3 Validity Issues in the Literatures Reviewed

Reliability is about how far a questionnaire or test produces the same results in repeated trials. Table 2.8 below shows the number of studies that dealt with the issues of validity and reliability. As Table 2.8 shows, in DCEs applied to health with specific reference to WTP or health insurance from 2001–2013, only 13 studies tested for reliability compared to two from 1990–2000. This shows that there has been much improvement in this area of the research. Since 1990, only three studies (Herbild et al., 2009; Singh et al. 1998; Chakraborty et al., 1993) have tested for external validity. As explained by Lancsar and Louviere (2008), the key reason for the low number of studies that tested for external validity in health is the lack of revealed preference data. Within the three periods reviewed, 1990–2000, 2001–2010 and 2011–2013, about 54.5%, 53.5% and 21.5% of the studies tested for internal validity respectively. The reason for its continuous use is that it handles two critical issues: first, it tests the statistical significance and the expected signs a priori, and second, it tests respondents' decision-making abilities and consistency. Alongside internal validity, tests for rationality (internal consistency) have also been used more frequently. These test the consistency of the questionnaire, i.e. whether respondents understand the choice questions given to them.

Table 2.8: Validity and Reliability Issues

VALIDITY AND RELIABILITY[1]	1990–2000	2001–2010	2011–2013
	N = 22 (%)	N = 158 (%)	N = 102 (%)
Reliability	2 (9.1)	6 (3.80)	6 (5.88)
External Validity	2 (9.1)	1 (0.63)	0 (0)
Internal Validity	12 (54.5)	84 (53.16)	22 (21.57)
✓ Theoretical	8 (66.7)	62 (73.8)	15 (68.20)
✓ Compensatory Decision Making	4 (33.3)	22 (26.2)	7 (31.80)
Face Validity	0 (0)	9 (5.70)	5 (4.90)
Convergent Validity	1 (4.5)	11 (6.96)	7 (6.86)
Rationality (Internal Consistency)	4 (18.2)	38 (24.05)	19 (18.63)
Predictive Validity	0 (0)	2 (1.27)	1 (0.98)
Not Stated	1 (4.5)	7 (4.43)	42 (41.18)

1. Some studies used more than one method.

The issue of the inclusion of a cost or monetary variable as one of the attributes of the DCE was also looked at. All the 199 studies reviewed used cost or another monetary measure as one of its attributes. This is due to the objective of this review, i.e. applying the DCE method to estimating WTP and other health outcomes.

2.3 DISCUSSION AND CONCLUSION

The main contribution of this chapter is to provide a detailed taxonomy of the application of DCE to WTP up to the period 2013.

The review shows that compared to the base period 1990–2000, the number of studies using DCEs and their application to WTP and health insurance has increased greatly. From 2001–2010, the number has increased considerably (over 650%) compared to the period 1990–2000. Comparing the period 1990–2000 to 2011–2013, one realizes that there has also been an increase of over 450% in the number of studies. This point to the fact that the use of DCEs in health related issues has increased greatly within the past decade.

DCEs continue to be a useful tool in health economics. There are several reasons for the increased use of DCEs: they mimic real choice behaviour; they estimate the importance of each attribute to the overall objective; they are used to estimate the MRS between attributes, which gives an indication of the extent to which respondents are prepared to trade attributes; they are used to ascertain the extent to which attribute levels need to change from their present status in order to improve the acceptability of services offered, allowing the respondent to choose the new service over the old one; they can be used to investigate consumer preferences for health care products and programs; they are used to compliment actual market data in health care; and they can be used to predict demand for healthcare products (Ryan and Gerard, 2003; Ryan et al., 2010).

The review shows that all the studies (199 papers) used a monetary attribute. This is because the objective of this work is to review DCE papers with reference to WTP and health insurance. The attributes time and others, including staff welfare, are the second most widely used attributes in the studies reviewed. Time includes but is not limited to waiting time for health outcomes, an appointment to see a doctor, the waiting time for results of surgery/tests, treatment time, the duration of benefit effect etc. Staff welfare on the other hand includes issues like staff promotion and housing, duration of service before further study, professional development etc. The study of human resource issues in health is new and earlier studies were conducted at the turn of the century. Since the early 2000s many studies have focused on this aspect of health. Hence, the increased use of attributes specific to human resource and job retention issues.

On the number of choice questions to handle, it is worth noting that the literature suggests that individuals can conveniently and reliably answer no more than 16 choice questions (Ryan and Gerard, 2003). However, this issue is context specific, and pilot tests should explore the optimal number of choices.

Fractional factorial designs are still widely used in health economics using DCEs. It is however important to note that all fractional factorial designs involve some loss of statistical information. According to Louviere et al. (2000), this loss of information can sometimes be important since fractional factorial designs limit the ability to note interactions between two or more attributes. They continue their argument by explaining that the exclusion of interaction effects does not necessarily lead to a biased result because of the following reasons: main effects typically account for 70%–90% of the explained variance; two-way interactions typically account for 5%–15% of the explained variance; and higher-order interactions account for the remaining explained variance.

Orthogonal main effect designs are still the most commonly used design method in DCEs because of their attractiveness to researchers, i.e. they are small in size even when the number of attributes and their levels are high; they avoid multicollinearity between attributes, and include an independent and consistent estimation of the attributes. The main effects (two-way interactions) are not widely used in the literature because according to Carson and Louviere (2011), the particular design the researcher may be interested in might not exist and one must assume the insignificance of unobserved interactions, which leads to bias from unobserved interactions that are significant.

The self-complete questionnaire is the most widely used data collection method applied in most of the studies under review. The mode of data collection is influenced by the objective of the study.

Software packages continue to be the most widely used method of designing DCEs. The focus in experimental design has shifted to efficient designs, hence the increased use of SAS. SAS from our review is still the most popular software used in experimental design. However, the software Ngene, also designed to enable efficient design is recommended, though not popular in the literature. Apart from SAS, SPSS is the second most widely used software in experimental designs. Louviere and Lancsar (2009) have noted the importance of research to identify conditions under which prior knowledge of parameters will improve design properties, especially where there is an increased use of software design to incorporate a priori information on parameters. This review, like others, finds that main effects models continue to dominate the types of effects used.

The RE probit model is the most widely used method in DCE model estimation. From table 2.7, it is clear that there has been a shift in model estimation techniques. Earlier stages of the application of the DCE method in health saw the popular use of binary choice estimation models as the DCEs had only two alternatives. However, the options increased to three or more, and allowed the use of MNL and CNL models. Recently, more advanced models to solve some of the problems inherent in MNL models have been used, for instance MXL, NL and Latent Class Models (LCM) models. These flexible models – MXL, NL and LCM – do come with their own challenges. These include making assumptions regarding which variable(s) to use as random and fixed, which coefficients to vary with which distribution, and the number of latent classes as well as an awareness that models can be over-fitted.

For methodological consideration, future work should make use of interaction terms in both the design and analysis of a DCE. Louviere and Lancsar (2009) and Johnson et al. (2013) maintain that identification is a crucial area for future research. Their recommendation as put by Lancsar and Louviere (2009) is that "one first focus on identification, and then on efficiency because one may be able to improve efficiency by increasing the sample size, but identification cannot be changed once a design is constructed" (pp. 536).

Another critical area that needs consideration in the application of DCEs is validity, especially external. Internal validity is most widely used in the literature while the use of external validity is limited. Very few studies have attempted to test for external validity. Ryan and Gerard (2003) pose a challenge to find imaginative solutions to test external validity but this idea is still highly under- researched as shown in our review. External validity should therefore be considered in future studies.

Despite its interesting results, this chapter has limitations. A methodological limitation of this study is its over-reliance on published sources. Other studies were left out because they were not published, hence limiting the accurate representation of the state of DCE practice due to publication lags. Another limitation is that this review has considered only published work in English, hence excluding non-English language literature

To conclude, we have seen that the application of DCEs to WTP and health insurance in health economics is gaining recognition as the number of studies continues to increase. DCEs remain a popular method of estimating WTP.

Appendix 2A: ***Studies in current review grouped according to objective***

A- Willingness to Pay

1. Managing poorly performing clinicians: Health care providers' willingness to pay for independent help. Health Policy 104 (2012) 260– 271. Watson V, Sussex J, Ryan M, and Tetteh E.
2. Preferences for long-term care services: Willingness to pay estimates derived from a discrete choice experiment. Social Science & Medicine 70 (2010) 1317–1325. Nieboer AP, Koolman X, and Stolk EA.
3. Socioeconomic Differences in Preferences and Willingness-to-Pay for Insulin Delivery Systems in Type 1 and Type 2 Diabetes. Diabetes Technology & Therapeutics Vol. 11, No. 9, 2009. Guimaraes C, Marra CA, Colley L, Gill S, Simpson S, Meneilly G, Queiroz RHC, and Lynd LD.
4. Does Attribute Framing in Discrete Choice Experiments Influence Willingness to Pay? Results from a Discrete Choice Experiment in Screening for Colorectal Cancer; Value in Health Volume 12 • Number 2 • 2009. Howard K and Salked G.
5. WTP for alternative Policies for Patients with Alzheimer's disease; Health Economics, Policy & Law (2008), 3: 257 – 275. Negri MA, Pinilla J, and Leon CJ
6. An Evaluation of Patients' Willingness to Trade Symptom-Free Days for Asthma-Related Treatment Risks: A Discrete Choice Experiment; Journal of Asthma, 45:630–638, 2008. Mctaggart – Cowan HM, Shi P, Fitzgerald JM, Anis AH, Kopec JA, Bai TR, Soon JA, and Lynd LD.
7. Validity and Reliability of Willingness to Pay Estimates from two overlapping Discrete Choice Experiments; Socioeconomic Institute, University of Zurich Working Paper No. 0412, 2008. Telser H, Becker K, and Zweifel P.
8. Willingness to Accept versus Willingness to Pay in a Discrete Choice Experiment; Volume 11 No.7 (2008) Value in Health. Grutters JPC, Kessels AGH, Dirksen CD, van Helvoort-Postulart D, Anteunis LJC, and Joore MA.
9. Willingness-to-pay for caregivers of children with asthma or wheezing conditions; Therapeutics and Clinical Risk Management (2007) 3(1) 157-165. Walzer S and P. Zweifel.

10. Conjoint Analysis of French and German Parent's Willingness to Pay for Meningococcal vaccine; Pharmacoeconomics (2007) 25 (2) 143 – 154. Bishai D, Brice R, Girod I, Saleh A and Ehreth J.
11. Patient preference and willingness-to-pay for Humalog Mix25 relative to Humulin 30/70: A multi-country application of a discrete choice experiment. Value in Health (2004) 7, 4, 442-454. Aristides M, Weston A, Fitzgerald P, Le reun C and Maniadakis N.
12. Discrete choice experiment to derive willingness to pay for methyl aminolevulinate photodynamic therapy versus simple excision surgery in basal cell carcinoma. Pharmacoeconomics 2004; 22 (18): 1195 -208. Weston A and Fitzgerald P
13. Willingness to pay for Complete Symptom relief of Gastro Oesophageal Reflux Disease (GERD) Archives of Internal Medicine (2002) 162, 1361-1366. Kleinman L, McIntosh E, Ryan M, Schmier J, Crawley J, Locke GR and de Lissovoy G.
14. Measuring willingness to pay for risk reduction: an application of conjoint analysis. Health Economics (2002) 11 (2), 129-139. Telser H and Zweifel P
15. Willingness to pay for improved respiratory and cardiovascular health: A multiple format stated preference approach. Health Economics (2000) 9: 295-317. Johnson FR, Banzhaf MR and Desvousges WH
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Chapter 3 – Willingness to Pay for Health Insurance among Informal Sector Workers in Sierra Leone: A Discrete Choice Experiment Approach

3.1 INTRODUCTION

Over 2 billion people living in developing countries are faced with health systems afflicted by inefficiency, poor quality services, inequitable access and inadequate funding; accounting for 92% of global annual deaths from communicable diseases, 68% from non – communicable conditions, and 80% from injuries (Escobar et al., 2010; World Bank 2010). The high out of pocket (OOP) payments for health care deter the poor especially those in the informal sector from accessing basic health care services.

Lack of access to health care and high health expenditures is discussed in the literature as one of the primary causes of poverty and deprivation of rural households in poor countries. As Justino (2007) explains, the poor are the ones living in extreme conditions of poverty and deprivation and they are found in very impoverished conditions characterised by lack of access to social and economic facilities coupled with job insecurity, hence making them to be vulnerable to shocks that eventually leaves them in abject poverty. This situation can be slowed down through improved health financing mechanisms like offering low-cost health insurance to low income households. Health insurance is central to improvements in the health status of a country's population, as it subsidises access to health services during periods of ill health (Escobar et al., 2010). Scholars argue that health insurance will play an important role in accessing medical care and reducing the high cost of OOP health expenditure, and preventing unnecessary deaths and increasing the economic well being of people.

The question therefore is, how much are people willing to pay for health insurance in such a setting? As health insurance is a non-marketed good, estimating willingness to pay for health insurance will be essential. Willingness to pay (WTP) is the most popular evaluation technique use to elicit preferences in health economics. WTP is a stated preference approach that estimates the maximum amount of money a person is willing to pay to obtain a particular benefit such as health insurance (Kielhorn and Schulenburg, 2000). WTP aims to determine how much individuals are prepared to pay to reduce their risk of mortality and morbidity from the present (Mooney, 2003). WTP can be estimated either through the contingent valuation method or the discrete choice experiment (DCE) method. The contingent valuation is a stated preference method wherein households are asked directly how much they are willing to pay for a good/service. It is called "contingent" valuation because people state how much they are willing to pay contingent on a particular hypothetical scenario and description of the commodity being valued (Ryan et al., 2010).

In this paper as stated earlier, we choose the DCE method over the contingent valuation method because: first, the DCE allow researchers to describe the incremental benefits that consumers derive from the different individual attributes of the good/service; second, the contingent valuation method has the potential for respondents to give biased answers to questions posed in the survey; and third, the DCE method can overcome some of the "biases" encountered in empirical applications using contingent valuation method (Hanley et al., 2001).

The objective of this paper therefore is to estimate WTP for health insurance among informal sector workers in Sierra Leone using the DCE approach. The key questions that this research tries to answer are, first, how much are households willing to pay for health insurance; second, whether location (rural or urban) matters in deciding WTP for health insurance among these informal sector workers and finally, which attribute informal sector workers are willing to trade the most. The paper is structured as follows: First, it provides some background into the DCE method used. Next we provide information about the experimental design and implementation use for the study. After the econometric specification, we present results in the form of WTP estimates, which are compared between locations and different informal sector activities. Discussion of results and conclusion are presented in the last section.

3.2 THE INFORMAL SECTOR OF SIERRA LEONE

The informal sector is formed either by the coping behaviour of individuals and families in economic environment where earning opportunities are scarce (such survival or coping activities include casual jobs, unpaid jobs, subsistence agriculture etc.) or it is a product of rational behaviour of entrepreneurs that desire to escape state regulations such as illegality in business (tax evasion, avoidance of labour regulations etc.) and activities not registered by statistical offices. Generally, the size of the informal labour market varies from the estimated 4 – 6% in the high - income countries to over 50% in the low - income countries.[16]

The International Labour Office (ILO) in 1993 (during the fifteenth international conference of labour statisticians) define informal sector as composed of entities engaged in the production of goods or services with the main objective of generating employment and income (R4D, 2013).

[16] Taken from the World Bank website www.worldbank.org and accessed on 12th September 2015.

These entities are to operate at two levels of organisations, with little or no division between labour and capital, and on a small scale. The labour regulations in these settings are based on casual employment, relatives, kinship, no contractual arrangements with formal guarantees etc.

Informal sector workers are subsistence households who are faced with risks and calamities such as sickness, famine, fire, flooding etc that can throw them into a state of permanent indebtedness. Arhin – Tenkorang (2001) explains that the informal economy is characterised with the following: deep fragmentation that is diverse; low, irregular and insecure employment; exposed to a variety of diseases and health risks; poor access to safe drinking water and sanitation facilities; overcrowding and poor housing hence making them vulnerable to waterborne and communicable diseases; high dependence on risk coping mechanisms such as selling their assets to be able to pay for medical treatment fees, hence the reason for their frequent visits to "quack" doctors.[17]

The informal sector in Sierra Leone is dominated by different kinds of small – scale enterprises and business activities. These activities include cookery, tailoring, carpentry, metal working, shoe making, baking, photography, watch and radio repairs, hair dressing, subsistence farming, commercial bike riding ("okada"), petty trading, cattle rearing etc (Kamara, 2008). Kamara (2008) opine that these enterprises together with their networks are the main contributors towards the development and the subsistence of these activities in the country. Due to its wider scope and variety of activities, the informal sector absorbs a seemingly unlimited number of people in different occupations. Petty trading is the hallmark of the informal sector in Sierra Leone (Kamara, 2008). The informal sector in Sierra Leone is characterised with increasing poverty and weak employment conditions. The World Bank estimates the size of the informal sector in Sierra Leone to be 45% of GDP. The informal sector in Sierra Leone consists of all economic activities outside the formal institutional framework and cuts across both the rural and urban informal sectors respectively. About two – thirds of the population in Sierra Leone lives in rural areas and are involved in informal sector activities (World Bank, 2013). People join the informal sector in Sierra Leone because majority of the students entering secondary schools do not go on educational programmes of their choice and those who continue the educational programmes, a good number of them also dropout either, for economic or social reasons. For the purpose of this paper/thesis, the informal sector in Sierra Leone is described as economic activities that include petty trading, subsistence farming, commercial bike riding ("Okada"), cattle rearing, fishing, tailoring, alluvial mining, and quarrying. A household whose main source of livelihood comes

[17] Quack doctors are untrained and unqualified so-called doctors who are found mainly in remote and rural areas.

from any of these activities are classed as informal sector households. Households found within these sectors are generally poor, not better educated, deprived economically (do not have access to credit) and socially (do not have access to health care due to it's high cost), hence considered to be informal sector households.

In almost all the formal sector employment arrangements, there is a contractual agreement between employers and their employees in terms of health care. One of the following arrangements is often agreed upon: the employer makes arrangement with a retainer for the company; employees are paid a medical allowance in their pay package; the employer employs an in – house medical team etc. However, such forms of arrangements are completely absent in the informal sector. Ghosh and Mondal (2011) explain that the informal sector workers coping with these vulnerabilities (flooding, fire accident, sickness, famine etc) and the lack of a special scheme and considerations for this population makes their living condition difficult. It is a wide belief among scholars that informal sector households facing poor health do not have recourse to mechanisms that will protect the necessary financial resources they require for basic consumption needs such as transportation, education and food. In addition, Arhin-Tenkorang (2001) explains that in poor African countries, there is the belief that informal sector workers cannot access appropriate health care at the point of need because of lack of money. Therefore access to health care is constrained by financial difficulties and limited accessible health facilities for these workers. It is therefore prudent to estimate willingness to pay for health insurance among informal sector workers in the northern and western regions of Sierra Leone.

3.3 METHOD

In this study we employ a DCE methodology to investigate household's WTP for health insurance (Vroomen and Zweifel, 2011).[18] DCEs are base on the idea that households derive utility not from a good per se but from the underlying attributes of the good (Lancaster, 1966). In this context therefore, DCEs present households with alternative descriptions of a health insurance scheme differentiated by combinations of attribute levels. Households are therefore asked to choose their preferred alternative. One of the main assumptions inherent in a DCE is, for each choice made, the chosen alternative is assumed to yield a higher level of satisfaction than the one rejected. This allows the probability of the chosen alternative to be modelled in terms of attribute levels.

[18] To the best of our knowledge, this is the only published paper that used DCE to estimate WTP for health insurance

Following Ryan and Gerard (2003), this study follows the five stages in undertaking a DCE. However, few issues come into mind when developing a DCE: first, to determine the overall policy objective and the type of choice experiment to be designed (Lancsar and Louviere, 2008; Ryan et al., 2010; and Johnson et al., 2013); and second, the researcher must be able to determine which design type to use, whether binary or multinomial design (Street and Burgess, 2007).[19]

3.3.1 Attributes and Levels

In this study, we ask households to make a choice between two health insurance schemes, A and B, which requires the use of a binary choice model.

First, we begin our study by identifying attributes to use in the DCE design. For this purpose, we search through the literatures and identify 10 attributes.[20] We sent the list to 50 households to rank the 10 attributes in order of importance. The main question we ask in the pre-test survey reads…

"Assuming a national health insurance scheme is to be introduce in the country, what are the key factors you will take into consideration before joining the said scheme, and from the list of attributes shown, please tick according to your order of preference".

The four most important attributes the households chose were coverage, waiting time, choice of health care provider and cost. Coverage as an attribute refers to the type of benefit the scheme will provide to members. Waiting time refers to the time it will take for a member to see a medical personnel upon their visit to a hospital or a health centre. Cost refers to the amount of money it will cost a household or premium to pay in order to benefit from the facilities provided by the scheme. The choice of health care provider refers to the type of health care insured people will be able to access. The cost of the scheme will have greater impact on whether a household will be willing to pay or not. Since one of the key objectives of this study is to estimate household's WTP for health insurance, this can only be done when cost is one of the attributes. So this explains why cost is chosen as one of the attributes. The choice of the attributes is based on policy relevance and feasibility of administration considering that the survey consists of personal interviews we carry out at home to the population we chose. These attributes are widely used attributes in the literature in estimating WTP. We also ensure that the attributes we chose are plausible, quantifiable and above all easily recognise by the respondents.

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[19] See appendix 3A for an analysis of steps to carry out in a DCE.

[20] The attributes include cost, coverage, choice of provider, waiting time, information, choice of drugs, new method of treatment, frequency in use of benefits, location of providers, and terminal diseases to be fully covered.

In line with the preceding argument and WTP studies in developing countries, we assign three levels to each of the attributes we chose. The final four attributes and their three levels each are shown in table 3.1 below.

Table 3.1: Attribute and Levels used in the study

Attributes	Attribute Levels	Description
Coverage	Simple Moderate Comprehensive	Outpatient treatment of minor diseases Doing minor operations and Inpatient treatment of minor diseases Major operations and inpatient treatment of diseases
Waiting Time	45 Minutes 60 Minutes 90 Minutes	The length of time one has to wait before seeing a medical personnel
Choice of Provider	Private Public Non-Public	Health centres and hospitals owned and operated by private people Health centres and hospitals owned and operated by Government Health centres and hospitals owned and operated by religious and other groups, i.e. not owned by government
Cost/Premium	4000SLL 6000SLL 10000SLL	The monthly premium a member will pay for the scheme

3.3.2 Experimental Design

After identifying the attributes and assigning levels to them, we proceed to generating the choice profiles through the use of an experimental design. The DCE includes four attributes each with three levels, resulting to 81 hypothetical health insurance profiles (# of Levels $^{\text{\# of Attributes}}$ = 3^4 = 81). To ensure the cognitive burden of respondents is reduced to a workable size, we use a fractional factorial design (FFD).[21] Applying the FFD, we reduce the number of profiles to a manageable number without losing the chance of estimating main effects in the design. The software SPSS is used to construct the experimental design. A total of 18 choice profiles are generated using the FFD, which are subsequently blocked into two blocks of 9 choice sets each. However, a tenth choice (dominant) question is included in each block to test for dominance effect, that is, to reflect on whether households understand the DCE questions. Hence, each

[21] A fractional factorial design involves the selection of a portion of all possible profiles, in which the properties of the full factorial design are maintained such that the effects of interest can be calculated as efficiently as possible.

household is presented with 10 choice questions – 9 for the main DCE and 1 to test the level of understanding of the questions.

A generic (unlabelled), forced - choice experimental design is employed in this study. An unlabelled experiment is one wherein the alternatives are not given any name that will make the decision maker know the alternatives being used. Ryan et al. (2010) posited that in a generic (unlabelled) design, respondent's focus more on the attributes which is preferred in estimating the marginal rates of substitution between attributes than the alternatives. Forced experiments constrain respondents to express a preference (i.e. make a trade – off among attributes) even when both alternatives are unattractive. Hensher et al. (2005) explained that by forcing respondents to make a choice, you are obliging them to trade off the attribute levels of the alternatives available and getting information on the relationship that exists between the attribute levels and choice. This study did not use the opt – out option because as discussed by Ryan and Skatun (2004), including the opt - out option will raise the number of neutral responses, that is, increasing the number of individuals that may choose the opt - out scenario to prevent them from making difficult choices, even when it will not result to the highest utility. This study also did not use the status quo option because as explained by Salked et al. (2000), it will result to "status – quo bias", that is, the tendency for respondents to choose what they know best, since they know the current health and health care facilities available to them. Table 3.2 below gives an example of a choice set as shown in the questionnaire.

Table 3.2: Example of a choice set used in the questionnaire

	Health Insurance Scheme A	**Health Insurance Scheme B**
Coverage[22]	Comprehensive	Simple
Waiting Time (Minutes)	45	90
Choice of Provider	Public	Contracted
Cost (SLL)	4000	6000
Which Scheme would you prefer		

All the attribute levels are presented and described to respondents before carrying out the choice experiments. The essence of this process according to Bateman et al. (2002) is to minimise the

[22] Moderate coverage is used as the definition of coverage right through out this work

size of 'warm glow' biases, which can affect stated preference methods. In addition to the choice questions, the questionnaire captured relevant socio-economic characteristics for each household. Based on the aforementioned, the efficiency of the experimental design compared to the full design is verified as 91.7%, using Street and Burgess (2007) website.[23]

3.3.3 Data Collection and Analysis

The sample needs and locations for this study was designed and provided by Statistics Sierra Leone (SSL) based on recent pre – census data that provides information on settlement names, population and household sizes. We use a two stage stratified random sampling method to identify the households. A sample size of 1670 informal sector households takes part in the study. The economic unit we use in this study is the household and is chosen randomly from both strata. The household and not individuals is the economic unit we use in this study because the economic decision to purchase health care among these rural and mostly farmer households is more likely to be a household decision rather than an individual.

The study focused on the Northern and Western Regions of Sierra Leone. The choice of these two regions is deliberate; the north has the poorest district while the Western Region is the richest region in the country.[24] Added to the above, as explained by Deaton and Paxson (97), the choice of a study area when purposively driven by the researcher's prior knowledge and familiarity, enhances the accuracy of the data to be obtained at least to a certain degree, and the econometric estimates obtained thereof.

Eight informal sectors are identified to be common within these two regions and used for the study, namely petty trading, subsistence farming, commercial bike riding (Okada) business, cattle rearing, fishing, tailoring, mining, and quarrying.

The questionnaire we develop is divided into three sections: (1) a question to help identify the informal sector the household is engaged in; (2) introduction to the DCE and the series of blocked choice questions to make a choice from; and (3) background questions on households socio-economic and demographic characteristics. We did a pilot study to test the attributes, their levels, the questionnaire and necessary corrections made before we undertake the final survey. To conduct the survey, we recruited 15 students from the medical school and department of economics of the University of the Sierra Leone to assist in the survey. We conducted the main

[23] http://crsu.science.uts.edu.ac/choice

[24] The political division of Sierra Leone is thus: sections form a chiefdom; chiefdoms form a district; and districts form a region.

survey within the period May and July 2013. Data entry staffs did the cleaning and entering of the data.

Since the questionnaire is interviewer administered, all the One thousand six hundred and seventy (1670) households sampled participated in the study. The dominance test result shows that 66 households (4.0%) did not pass and hence their data are discarded. 1604 household's data are however left for cleaning and analysis. During the data cleaning process, 146 household's data are incomplete and are hence left out for the final analysis. Therefore, we use only data for one thousand four hundred and fifty eight (1458) households in the study. This imply 26244 observations are used for the data analysis, that is, 1458 households * 9 choice sets * 2 alternatives. We use a random effect logit econometric model as a base for the analysis using STATA version 13.1.

3.3.4 Model Estimation

Once the DCE is devised and the data collected, discrete choice modelling within a random utility maximization (RUM) framework is use to analyse responses obtained from DCEs. The theoretical basis for our model estimation is based on the RUT (McFadden, 1974), which explains that the choice of Health Insurance Scheme is made based on the scheme with the highest utility.

It is widely supported in the literature that the appropriate discrete choice technique to use depends on the kind of method used to collect the data. Generally, there are two broad families of collecting discrete choice data, that is, binary choice data or multinomial - choice data. Since each household is asked to choose between two alternatives, that is, health insurance A or B, hence, a binary choice model is therefore appropriate. Each household has to evaluate 9 different choices of health insurance questions; the data therefore is of a panel type.

Discrete choice – based approaches are based on random utility function, which shows the level of utility a household derives from choosing a health insurance scheme. The utility is derived from the services associated with the health insurance scheme.

The latent utility of household i to choose alternative j (that is, health insurance schemes A or B) can be divided into two separate components: an observed component of indirect utility, V_{ij} and a random or residual unobserved component, ε_{ij}, such that

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{3.1}$$

where U_{ij} is the utility that household i gets from choosing health insurance scheme j and ε_{ij} is the idiosyncratic error.

However, the observed component of indirect utility is assumed to be linear in the parameters and linear in the attributes of the health insurance scheme, such that for a given attribute level *X,* of each alternative (health insurance scheme) *j* and their corresponding parameters, β, we have

$$V_{ij} = \beta_i X_{ij} \tag{3.2}$$

where β_i represents the marginal utility parameters that are interpreted as relative importance weights; and X_{ij} is a vector of observed attributes.

The error term ε_{ij} in equation 3.1 is assumed to be a logistic distribution. We control for potential correlation in the responses of each household (the household specific variation) by introducing fixed effect α_i. The unobserved error terms are represented by α_i and ε_{ij}, where α_i is the household specific error term due to differences amongst respondents (resulting from measurement error) and ε_{ij} is the random error term because of the differences among observations (the common error term that may also vary across scenarios) (Manski, 1977), such that our random effect model becomes

$$U_{ij} = \beta_i X_{ij} + (\alpha_i + \varepsilon_{ij}), \tag{3.3}$$

Each household's choice between the alternatives (health insurance schemes A or B), treated as a single observation, is included in the model as a binary dependent variable such that "1" represents a health insurance scheme being chosen, and "0" otherwise. A random effect logit model is used for the estimation because of the following: to represent the distribution of the error term that was assumed to be a logistic distribution; to estimate the parameters β_i in order to capture the within – household correlation; and also to account for the multiple observations from a single household. We assume that the utility of a household is a linear and additive function wherein a change in the level of one attribute does not affect the marginal utility of another attribute. We also assume that the household's socio – demographic characteristics will also influence the choice of a health insurance scheme. However, we find them not to be statistically significant and therefore we dropped them from our model. Following Seghieri et al. (2014), Campbell (2006), Moia et al. (2013) and Hanson and William (2010), our final random effect logit model for estimation is therefore given thus

$$U_{ij} = \beta_0 + \beta_1 Cov_{ij} + \beta_2 Cost_{ij} + \beta_3 Pubchh_{ij} + \beta_4 Contchh_{ij} + \beta_5 Wait_{ij} + \alpha_i + \varepsilon_{ij} \qquad (3.4)^{25}$$

where the subscripts i and j represents the household and choice of health insurance scheme respectively; correlation $(\alpha_i + \varepsilon_{ij})$ = ρ, which takes account of the correlation among household's choices; β_0 *is* the constant term that captures the overall performance of Health Insurance B over

[25] Contracted choice of provider is replaced with non-public provider to give a better understanding to the reading. Therefore, contracted choice of provider is changed to non-public provider right through this chapter.

A when all the attributes in the model are fixed. Scott (2001) explained that the constant term is included in a DCE model to test and control for model misspecifications that arises from either unobserved dimensions or unobserved interactions between household's socio – economic/demographic characteristics and dimensions. The coefficients, $\beta_1 - \beta_5$ are marginal utility parameters that are interpreted as relative importance weights; Cov_{ij} refers to coverage, $Pubchh_{ij}$ refers to a household choosing public provider, $Contchh_{ij}$ refers to a household choosing a non-public provider, and $Wait_{ij}$ is the waiting time.

To determine WTP for any of the attributes for a household, following equations 3.1 – 3.4, we can get the following formula for WTP for household *i* for an improvement in say coverage;

$$WTP_i = \frac{\mathrm{dV/dcov_i}}{\mathrm{dV/dcost_i}} = \frac{\beta_{Cov_i}}{\beta_{Cost_i}} \quad (3.5)$$

However, the probability of a household choosing Health Insurance A using the logit model will be equal to the following notation:

$$P_{iA} = \frac{e^{V_{iA}}}{\sum_{j=A}^{J} e^{V_{iJ}}} \quad (3.6)$$

The sign and the statistical significance of each estimated coefficient is used to quantify the relative importance of the attributes and their marginal rates of substitution (MRS). The MRS that is embedded in Lancaster's theory of demand (Lancaster, 1966) shows how respondents are willing to trade an improvement in one attribute in order to forgo the other attribute.

The results of the survey are analysed using the random effects logit model in STATA/SE 13.1. The dependent variable is choice (choosing between health insurance A or B) and it is binary.

3.4 RESULTS

3.4.1 Descriptive and Summary Statistics

We use a total of 1458 household's data giving 26244 responses for the final analysis of the study. 212 households (12.7%) either did not pass the dominance test, meaning they did not understand the DCE questions, or have incomplete data; hence there responses are excluded from the data. Table 3.3 below presents descriptive statistics of the distribution of the household characteristics by location, that is, whether rural or urban. From table 3.3 below, we see that out of the 1458 household's data used, about 983 households (67%) live in rural areas whereas 473 households (33%) live in urban areas. In terms of region, about 57% (835 households) of our sample is found in the western region of Sierra Leone whereas about 43% (623) is found in the north. Looking at the distribution of our sample by districts, we see that about 44% of the sample comes from the western area district which includes Freetown, mountain and peninsula rural villages. Within the northern province, Bombali district has the largest sample size. This is so because Bombali district hosts the provincial headquarter city, thus giving more preference to sample more households here; the same can be said of Freetown.

Few interesting results are worth mentioning; first, over two – thirds of household's informal sector activities comprise petty trading, subsistence farming and commercial bike riding (Okada). This is clearly the case as majority of informal sector households in Sierra Leone are engaged in any of these three activities. The sectors, informal households are least predominant in are cattle rearing and quarrying. For rural households, we see that the sectors, petty trading, subsistence farming and 'okada' are the predominant activities (about 66.3%) whereas for urban areas, about 75% of households are engaged in these sectors. About 85% of the households go to health centre, hospital or pharmacy for medical treatment.

Table 3.3: Distribution of Households by Location

Variable	Frequency	Main Sample N = 26244 (%)	Rural N = 17694 (%)	Urban N = 8550 (%)
Location - Rural	17694	67.42	100	0
Location – Urban	8550	32.58	0	100
Region – North	11214	42.73	39.8	48.8
Region – West	15030	57.27	60.2	51.2
Bombali District	3330	12.69	12.6	12.9
Kambia District	1530	5.83	5.6	6.3
Koinadugu District	1962	7.48	6.5	9.5
Port Loko District	2412	9.19	8.0	11.6
Tonkolili District	1980	7.54	7.0	8.6
W.A. District	11484	43.76	42.7	45.9
Waterloo District	3546	13.51	17.5	5.3
Petty Trading	7074	27.0	27.2	26.5
Subsistence Farming	5184	19.8	16.4	26.7
'Okada'	5886	22.4	22.8	21.7
Cattle Rearing	1296	4.9	5.1	4.6
Fishing	2052	7.8	9.0	5.5
Tailoring	2754	10.5	11.1	9.3
Mining	972	3.7	4.8	1.5
Quarrying	1026	3.9	3.8	4.2
School	17712	67.5	69.5	63.4
No School	8532	32.5	30.5	36.6
Self Treatment	702	2.7	3.3	1.5
Traditional Treatment	666	2.5	3.0	1.7
Health Centre	12816	48.8	50.7	45.1
Hospital	6480	24.7	19.8	34.7
Drug Peddlers	2124	8.1	10.0	4.2
Pharmacy	3438	13.1	13.2	12.8
None	18	0.1	0.1	0.0

Table 3.4 below, on the other hand presents the summary statistics for the socio-demographic variables of our survey. For each variable, we present the means for each household based on their location, either in rural or urban areas, their mean differences, standard error and statistical significance. Overall, the result show that the distribution of the health insurance scheme attributes and household characteristics significantly varies between households that live in rural and urban areas.

Table 3.4: Sample Means by Location

Variables	Rural (N = 17694)	Urban (N = 8550)	Mean Difference (Rural – Urban)	Standard Error of Difference of Means[1]
Cost	6666.82	6666.36	0.46257	32.85452
Coverage	0.00158	-0.00327	0.00486	0.01075
Waiting Time	64.95	65.10	-0.15005	0.24641
Public Provider	0.33499	0.32990	0.00509	0.00621
Non Public Provider	0.33330	0.33341	-0.00012	0.00621
Petty Trading	0.16379	0.26734	-0.10354	0.0052***
Subsistence Farming	0.27158	0.26535	0.00623	0.287
‘Okada’	0.22789	0.21682	0.01107	0.00549**
Cattle Rearing	0.05087	0.04631	0.00456	0.00285
Fishing	0.08953	0.05473	0.0348	0.00353***
Tailoring	0.11089	0.09262	0.01827	0.00404***
Mining	0.04782	0.01474	0.03308	0.00248***
Quarrying	0.03764	0.04210	-0.00446	0.00255*
No Education	0.30521	0.36627	-0.06107	0.00616***
Primary Education	0.06511	0.06947	-0.00436	0.00328
Adult Education	0.19533	0.09894	0.09640	0.00484***
Basic Education	0.37026	0.38534	-0.01508	0.00638**
Secondary Education	0.06409	0.07999	-0.01590	0.00334***
Household Size	5.01	5.12	-0.11152	0.03063***
Age of Household Head	42.83	44.99	-2.16005	0.17406***
Remittance Received	37316.46	76415.63	-39099.17	1613.89***
Household Expenditure	370032.4	378174.20	-8141.81	1539.86***
Diseases:				
Malaria/Typhoid	0.72837	0.74740	-0.01903	0.00581***
Distance to Health Centre	2.13	2.19	-0.03742	0.03415

1. The differences are significant if $***p<0.01$; $**p<0.05$; $*p<0.1$

There are statistically significant differences between rural and urban households except for the following: attributes of the health insurance scheme (cost, coverage, waiting time, public and non-public providers); petty trading and cattle rearing informal sector activities; distance to the nearest health centre and primary education.

Households in rural areas have more often than those in urban areas heads of the households with adult education. The sectors that are significantly predominant in rural areas are “okada”, fishing, tailoring and mining. In contrast, households who live in urban areas tend to be significantly found more in the sectors, petty trading and quarrying, than rural counterparts; they significantly have a larger household size (this imply they have more members than rural households); and tend to have secondary education significantly more often than those in rural areas. In addition, households in urban areas are significantly older than their rural counterparts; they significantly receive more often remittances from family or friends; they have a significantly higher household expenditure per month than rural households; and suffer more often significantly from diseases (malaria or typhoid). To put into perspective, the mean number of households with at least secondary education, paid for free health care services (even though supposed to be free) and suffered from either malaria or typhoid fever is higher for urban households than their rural counterparts by about 24.8%, 7.4% and 2.6% respectively. For households that live in rural areas, their average number of households with adult education is 49.3% greater than urban households

3.4.2 Regression Results

The analysis of the data generated by DCE applies a random effect logit regression model. This regresses the choice of health insurance scheme on the attributes of the health insurance scheme, namely cost, coverage, waiting time, public choice of health care provider and non-public provider. The first part of the analysis looks at the regression results for the entire sample and the segmented samples - by type of location and informal sector activity.[26] Second, we estimate household's overall WTP using our sub - samples as well. The third part of the analysis looks at welfare changes and theoretical validity of the model.

The model as described in equation 3.4 is run using the statistical software STATA version 13.1 and the data generated thereafter. For the overall sample, the attributes are statistically significant at the 95% confidence level. The statistical significance of each attribute is tested using the Wald test. Results show that all attributes used are statistically significant (≤ 0.05), recognising that the type of coverage, cost of the health insurance scheme, public provider, non-public provider, and waiting time all significantly influence a household's choice of health insurance scheme (see table 3.5).

Table 3.5 below summarises the results of the final logit model used to analyse the impact of each attribute on the choice of a health insurance scheme. The logit coefficient shows the direction of the effect of each attribute on the choice of a health insurance scheme. The negative cost and waiting time coefficients are in line with theory; the higher the cost of a health insurance scheme, the less likely people are WTP for it and the reverse holds true. On the area of waiting time, the

[26] We are interested in estimating WTP for each informal sector in order to know which sectors are WTP more than the others and to guide policy makers in targeting the various sectors. We need this kind of information also for planning cooperative insurance schemes, which are based on occupations and are becoming common in SSA.

lower the waiting time, the more likely people are WTP for the scheme. The positive coverage coefficient indicates that household's prefer an improvement in coverage than not having any improvement in coverage. The results show that the attributes coverage and non-public provider significantly influence the household's choice of health insurance more than the other attributes. These results are in line with expectations and therefore provide support for our model.

Table 3.5: **Regression Results: Main Sample and by Location**

	Main Sample		Rural Household		Urban Household	
Choice	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Coverage*[27]	0.54596	0.01624***	0.52670	0.02218***	0.57192	0.02393***
Waiting Time	-0.00793	0.00071***	-0.00664	0.00096***	-0.00952	0.00104***
Pub Provider	0.05376	0.01590***	0.03083	0.02179	0.08071	0.02329***
NonPub Provider	0.5650	0.01641***	0.44470	0.02225***	0.70485	0.02446***
Cost	-0.00009	5.33e06***	-0.00009	7.28e06***	-0.00008	7.84e-06***
Constant	0.75884	0.06273***	0.68839	0.08521***	0.850002	0.093005***
No of Obs.	26244		13770		12474	
Wald chi2 (5)	2553.25		1121.51		1472.88	
Prob > chi2	0.0000		0.0000		0.0000	
Log Likelihood	-16713.37		-8912.80		-7762.7474	

***Indicates significant at p<0.01; * Coverage here refers to Moderate Coverage

From table 3.5 above, we can see results for part of our segmented model – type of location. Comparing results for both location, few issues are worth mentioning; first, all the attributes significantly influence the choice of a health insurance scheme except public provider for rural households that is not significant. Second, coverage and type of provider (public and non-public) positively influences the probability of choice of health insurance scheme. On the other hand, cost of the scheme and waiting time negatively influences the probability of choice of a scheme.

From table 3.5 above, we also realize that the coefficient for the attribute coverage even though it is a bit higher for urban households, is almost the same for both locations, implying households

[27] When we use any two kinds of coverage (simple and moderate; simple and comprehensive; and moderate and comprehensive) at any point in our regression, the results obtained move in the opposite direction of theory. For instance, we expect cost to be negative and coverage (of any kind) to be positive, but the result gives the opposite. Therefore, one type of coverage (moderate) was used right through and our results hinges on this. See appendix 3C for result when both attributes were used.

irrespective of their location place almost equal preference to type of coverage provided. On the other hand, urban households place more emphasis on the non-public type of provider than their rural counterparts. Urban households overall prefer this attribute than the rural households due to their level of awareness/understanding. The number of households that listens to a radio and read a newspaper captures this in the survey.[28] From the results in tables 3.5 & 3.6, we will observe that households prefer public and non-public providers to private providers. The reason is that informal sector households are certain of the fact that the private provider is not within their reach and it is not available where majority of them lives – rural areas. The few private providers are found in the cities. Therefore, the private provider is not a priority for informal sector households as evidenced by their WTP.

We want to know how the various informal sector workers behave in their choice of health insurance scheme. Table 3.6 below presents the econometric results.

Table 3.6: Regression Result for Informal Sector Economic Activities

	Petty Trading	Subsistence Farming	"Okada"	Cattle Rearing	Fishing	Tailoring	Mining	Quarrying
Choice	**Coef. (se)**	**Coef. (se)**	**Coef. (se)**	**Coef. (se)**	**Coef. (se)**	**Coef. (se)**	**Coef. (se)**	**Coef. (se)**
Coverage	0.49114	0.56729	0.64705	0.64797	0.41015	0.52561	0.9838	0.21560
	(0.03126)***	(0.03593)***	(0.0355)**	(0.0755)***	(0.0569)***	(0.0503)***	(0.0942)***	(0.0783)***
Waiting Time	-0.010	-0.00566	-0.01098	-0.01027	-0.00605	-0.0061	-0.0041	0.00173
	(0.00136)***	(0.00156)***	(0.00155)***	(0.0033)***	(0.0025)**	(0.0022)***	(0.0040)	(0.00341)
Public Provider	-0.04688	0.05964	0.07369	0.17021	0.15714	0.1587	-0.0369	0.05736
	(0.03057)	(0.03549)**	(0.0343)**	(0.0728)**	(0.0562)***	(0.0492)***	(0.0885)	(0.0779)
Non-Public	0.55083	0.36366	0.7604	0.70239	0.56888	0.6452	0.6480	0.27672
Provider	(0.03160)***	(0.03586)***	(0.03641)***	(0.0771)***	(0.0577)***	(0.0510)***	(0.0930)***	(0.0782)***
Cost	-0.00008	-0.00007	-0.00009	-0.00013	-0.00005	-0.00008	-0.00023	-0.00005
	(0.00001)***	(0.00001)***	(0.00001)***	(0.00002)***	(0.00002)***	(0.00002)***	(0.00003)***	(0.00003)**
Constant	0.89391	0.43303	1.00145	1.1940	0.57384	0.6898	1.0805	0.11073
	(0.12149)***	(0.13699)***	(0.13805)***	(0.2926)***	(0.2198)***	(0.1942)***	(0.3521)***	(0.30114)
No of Obs	7074	5184	5886	1296	2052	2754	972	1026
Wald chi2 (5)	703.8	381.17	797.78	159.47	151.98	269.82	178.39	24.20
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002
Log Likelihood	-4496.427	-3383.0725	-3582.76	-800.3309	-1338.005	-1752.665	-549.75	-698.693

***p<0.01; **p<0.005; *p<0.1

[28] In the survey, we asked households whether they listen to the news or read newspapers. If the person answers yes, then it means they are often aware of currents issues and development in the country.

From table 3.6 above, we observe that all attributes are significant for the various informal sectors except for the following; petty trading wherein public provider is not significant; mining and quarrying wherein waiting time and public provider are not significant. Mining and quarrying are similar activities for which the effect of the attributes is not surprising. For the following informal sectors - petty trading, “okada”, cattle rearing, fishing, tailoring, and quarrying – the non-public provider is the most significant attribute that determines the choice of a health insurance scheme. What is common about these sectors is that they operate in urban areas or very close to urban areas and they are the ones that have used hospitals more than their rural counterparts, hence them preferring a non-public provider. The sectors subsistence farming and mining are key rural economic activities, which explain to a greater extent their preference for the type of coverage than the other attributes.

3.4.3 Marginal Rates of Substitution

The DCE allows estimating the marginal rate of substitution (MRS), which is the rate at which a household is willing to substitute one attribute in order to get one unit of the other attribute. It is the absolute value of the negative of the ratio of any two attributes used in the study. The direction of the interpretation depends on what the denominator is. This study looked at the MRS of the public choice of provider and the non-public choice of provider for waiting time which is given as: [-($\beta pubchh/\beta w\_time$) and $[-(\beta contchh/\beta w\_time)]$. This basically shows how many minutes of a time a household is willing to give up in order to see a medical personnel for both public and non-public providers. Table 3.7 below gives the result for the main sample, rural households and urban households.

Table 3.7: MRS / Trade – offs between Attributes

Sample	Pubchh (Minutes)	Contchh (Minutes)
Main	7	71
Rural	5	67
Urban	9	74

Table 3.7 above shows the number of minutes on average a household is willing to give up beyond the normal waiting time to see a medical officer for both type of providers. For a public provider, the average household is willing to give up about 7, 5 and 9 minutes of their time to see a medical personnel for the main, rural and urban samples respectively. However, the story is different for the non-public provider wherein the average household is willing to give up more

than an hour. Comparing both the urban and rural households, the urban household is willing to wait about 7 minutes more than their rural counterpart. This again supports earlier points that the urban household considers the attribute – non-public provider highly than their rural counterparts.

3.4.4 Willingness to Pay

After estimating the MRS, we then proceed to calculate the willingness to pay. We estimate WTP by replacing the denominator of the MRS with the variable cost. The WTP for health insurance is the amount of money a household is willing to forgo each month in order to attain an improvement in their health status. It is the monetary value households place on each health insurance attribute. Table 3.8 presents household WTP results for the main sample and type of location (see Appendix 3B for individual WTP estimates).

Table 3.8: **Household WTP Estimates**[29]

	Main Sample		**Rural Location**		**Urban Location**	
Attributes	**WTP**	**% of Income**	**WTP**	**% of Income**	**WTP**	**% of Income**
Total WTP[1]	68657	20.7	54591	16.5	87404	26.4
Coverage	31965	9.6	28500	8.6	36568	10.8
Public Provider	3148	0.9	1668	0.5	5160	1.5
Non-Public Provider	33080	9.9	24063	7.3	45067	13.3
Waiting Time[2]	464	0.1	360	0.1	609	0.2

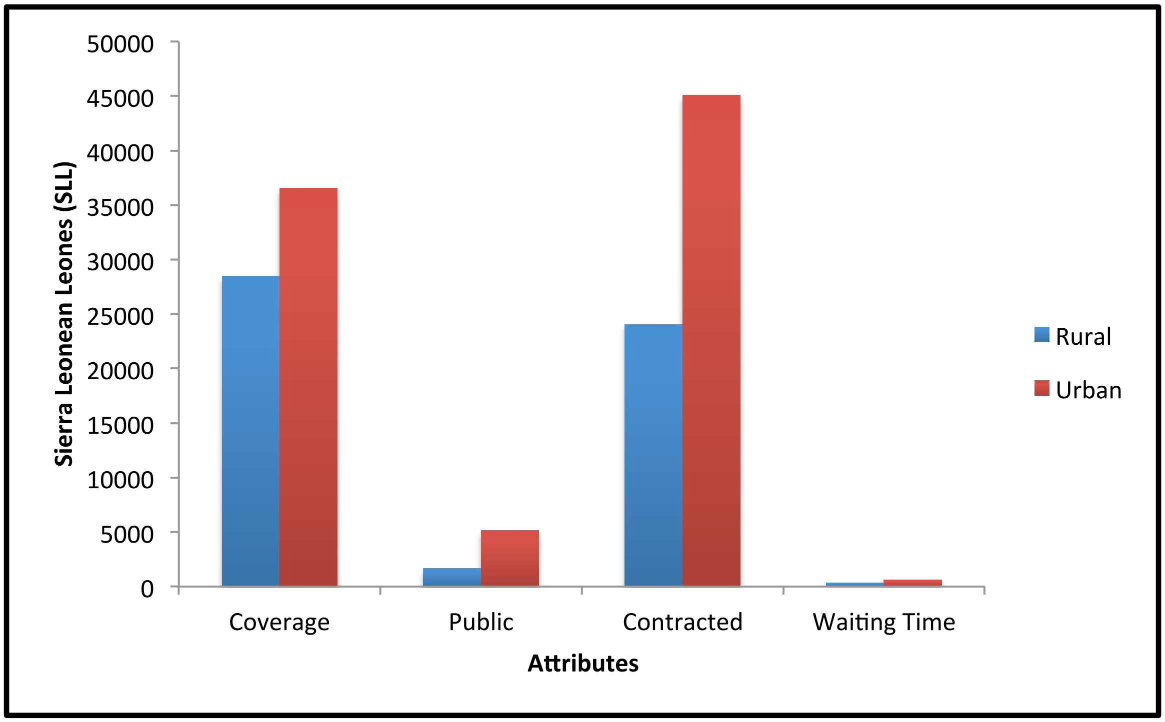
The WTP figures are in Sierra Leone's local currency – Leones.
1. The total/overall WTP includes an improvement in coverage, having both public and non-public providers, and a reduction in waiting time.
2. Whilst these ratios will result in negative WTP, representing what individuals would need to be compensated for an increase in waiting time, the figures represented show WTP for a reduction in waiting time.

Overall, households WTP is 68657SLL/$15.6/$3.1 per person (about 20.7% of their income) for health insurance which is in line with similar studies such as Dong et al. (2003), on Burkina Faso with an individual WTP of $3.17 and $4.25 using take it or leave it (TIOLI) and bidding games respectively; Asfaw et al. (2009) in their work on WTP for health insurance in Namibia found that over 50% of uninsured respondents are WTP $6.60 per month; Donfouet et al. (2011) in their study concluded estimated that rural households are WTP $2.15 per person/month for health insurance (See appendix 3D for Total WTP using different attribute packages). On average, households are WTP 31965SLL/$7.26 (about 9.6% of average household income) for an

[29] We assume a household has 5 members, as it is the average household size in our survey.

improvement in coverage, 33080SLL/$7.52 (about 9.9% of household income) for having a non-public health care provider, 3148SLL/$0.72 (about 1% of household income) to have a public health care provider and are WTP 464SLL/$1.1 (about 0.1% of income) for a minute reduction in waiting time.[30] There are vast differences in households WTP across locations. Urban households are WTP about 28% more than rural households for an improvement in coverage; they are also WTP about 2 and 3 times more to have a non-public or public provider respectively. Urban households are also WTP about 249.SLL/$0.1 more than their rural counterparts for a minute reduction in waiting time. However, comparing rural to urban households, the latter is willing to pay 32315SLL/$7.34 (about 9.5% of urban household income) more than what their rural counterparts are WTP. Figure 3.1 presents a succinct picture of WTP for health insurance by type of location.

Figure 3.1: Household's WTP for Health Insurance by type of Location

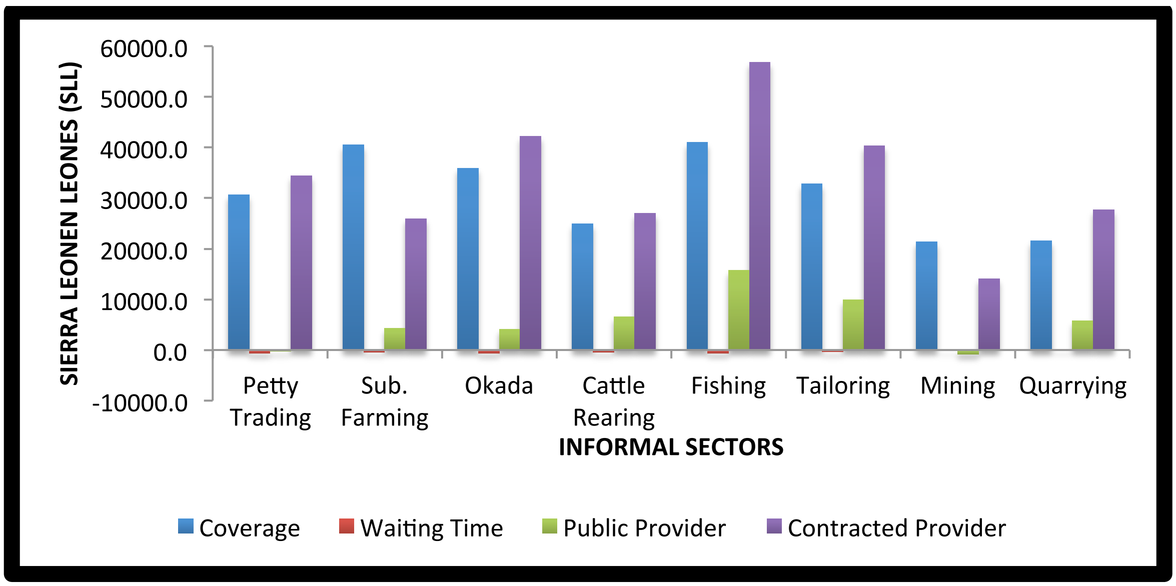


From figure 3.1 above, it is evident that urban households are WTP more for an improvement in coverage or for having a public or non-public choice of providers. From figure 3.2 below, result show that household's engaged in fishing are WTP higher than in the other sectors to have a non-public type of provider; households in fishing and subsistence farming sectors are WTP more

[30] An exchange rate of 4400SLL to $1USD was used.

than in all other sectors for an improvement in coverage; households in the fishing sector are WTP more than in all other sectors to have a public type of provider; and all other sectors except quarrying are willing to accept (WTA) a compensation for an increase in waiting time while those in the quarrying sector are WTP more for a reduction in waiting time. This shows that households engaged in quarrying value waiting time highly than the other sectors (shown by the negative WTP for waiting time). The results are as expected because we expect those households whose informal activity is primarily based in urban or semi-urban locations should be willing to pay more. It turns out that these urban - based informal sectors (fishing, "okada" and petty trading) apart from subsistence farming are WTP more for health insurance. This can be attributed to their better level of awareness, education, and better levels of income compared to those living in rural areas.

Figure 3.2: WTP by Type of Informal Sector Activity



We estimate Willingness to Pay (WTP) for households based on income levels. It is a strong theoretical point that as households' income increases, they are WTP more for health insurance. To go about solving this, we generate four income levels and we define them as follows:

Income Level One: 75000 – 218750SLL

Income Level Two: 218751 – 362500SLL

Income Level Three: 362501 – 506250SLL

Income Level Four: 506251 – 650000SLL

After generating the income levels, we use the random effect logit model to analyse the impact of each attribute on the choice of a health insurance scheme. The result for this regression analysis is shown in appendix 3E. However, we use this result to estimate WTP for each attribute based on the defined income levels. The WTP results therefore, are shown in table 3.9 below.

Table 3.9: WTP by Income Levels

Attributes	**Income Level 1**		**Income Level 2**		**Income Level 3**		**Income Level 4**	
	WTP (SLL)	**Percent of Income**	**WTP (SLL)**	**Percent of Income**	**WTP (SLL)**	**Percent of Income**	**WTP (SLL)**	**Percent of Income**
Coverage	5777.25	3.37	6790.67	2.27	6603.78	1.59	7124.57	1.28
Waiting Time[1]	(87.25)	0.05	(96.67)	0.03	(104.33)	0.03	(17.29)	0.003
Non-Public Provider	10426.38	6.09	15808.78	5.30	12956.11	3.12	13713	2.47
Public Provider	(970.75) [2]	0.57	2500.22	0.84	3066.44	0.74	2857.14	0.51
Total WTP	15320.13	8.94	25196.34	8.44	22731	5.50	24712	4.44
Average Income	171284.4		298500		415633		556185	
No of Observation	3924		11736		9054		2412	

SLL refers to Sierra Leonean Leones (local currency in Sierra Leone)

1. Whilst these ratios will result in negative WTP, representing what individuals would need to be compensated for an increase in waiting time, the figures represented show WTP for a reduction in waiting time.
2. Whilst this represents a negative WTP, it represents what households are WTP for not having a public provider

From the results in table 3.9 above, we can make the following conclusions. First, those households' on a lower income (income level one, with an average income of 171284.4SLL) are WTP about 15320.13SLL for an improvement in coverage (from moderate to comprehensive), a reduction in waiting time, having a non-public provider (as against not having a private provider), and not having a public provider. However, when their income increases (say income level four, with an average income of 556185SLL), they are WTP a higher amount of about 24712SLL. This implies, as income increases, households are WTP more for health insurance, which is in line with theory. Secondly, households on lower incomes (income level one), even though they pay a comparatively lower WTP amount, however, the amount they pay, takes proportionately higher percent off their income (8.94%). However, when their income increases (say income levels three and four), even though they have a higher WTP amount, yet it takes a proportionately lower percent of their incomes (5.5% and 4.44% for income levels three and four respectively).

3.4.5 Welfare Changes

One of the primary reasons for using DCEs and WTP is to enable researchers to predict probabilities and estimate welfare changes for new health care policies being introduced. After probabilities have been predicted, welfare changes are estimated using compensating variation (CV). When there is a policy change, there are winners and losers. The monetary equivalent for a particular loss of utility emanating from the introduction of a new policy say, a shift from health insurance scheme A to health insurance scheme B is called compensating variation. It is the amount to compensate consumers for the welfare loss induced by switching to a new health care policy (Health Insurance B). It is an ex ante measure of welfare.

Consider a best and worst case hypothetical policy scenarios: the first scenario which is considered the initial level and worst case provides moderate coverage wherein households can go to a public provider, with a waiting time of 90 minutes and it will cost the household 10000SLL per member while the other scenario (best case) provides a moderate coverage by a non-public provider with a waiting time of 45 minutes and it will cost the household 4000SLL per member.

The probability of choosing a public health care provider (Pubchh) and a non-public provider (Contchh) can be estimated thus using equation (3.6) above. We can also estimate the change in welfare as a result of a change in health policy – switching from a public provider scheme to a non-public provider scheme. Following Small and Rosen (1981) in Ryan et al. (2010), the compensating variation (CV) is used to estimate the change in welfare as a result of a change in policy. The Small and Rosen method for the estimation of CV as used here is stated thus:

$$CV \quad = \frac{\mathbf{1}}{\boldsymbol{-\beta cost}}[ln(\Sigma e^{Vcontchh}) - ln(\Sigma e^{Vpubchh})] \qquad (3.7)$$

where ln ($e^{Vcontchh}$) is the welfare gained or lost for the change to non-public provider whereas ln ($e^{Vpubchh}$) is the welfare gained or lost for having the old system – public health care provider. Table 3.10 below shows the result of our hypothetical case above.

Table 3.10: Probabilities and Compensating Variation (CV) for Hypothetical Case[31]

Sample	Probabilities		Compensating Variation	
	Pubchh	Contchh	CV (SLL)	CV (USD)*
Main	0.37490	0.62510	10180.42	$2.3
Rural	0.39799	0.60201	9235.18	$2.1
Urban	0.34884	0.65116	11477.51	$2.6
Petty Trading	0.35487	0.64513	11496.51	$2.6
Subsistence Farming	0.42457	0.57543	9491.67	$2.2
Okada	0.33477	0.66523	11223.38	$2.6
Cattle Rearing	0.37001	0.62999	9557.42	$2.2
Fishing	0.39849	0.60151	11296.43	$2.6
Tailoring	0.38072	0.61928	9377.16	$2.1
Mining	0.33517	0.66484	6786.02	$1.5
Quarrying	0.44538	0.55462	4408.03	$1.0

* Assuming exchange rate of 4400SLL to $1

Following the estimated utilities, it is evident that a rational household prefers a non-public to a public type of provider scheme since it provides better attributes. The probabilities show that ceteris paribus, the chance for a household to choose a non-public provider is about twice the chances for a public provider to be chosen. The probability for a household choosing a non-public provider is higher for urban than rural households whereas the probability of choosing a public provider is higher for rural than urban households. An explanation for this is that households in urban locations have a higher level of awareness than their rural counterparts. When comparing the various informal sectors, the story is the same. The probability for non-public provider is higher for "Okada" informal sector, petty trading and mining. These are sectors predominant in urban areas, especially the first two. However, the probability of choosing public provider is higher for households in informal sectors predominantly in rural settings or just outside urban areas, (quarrying, subsistence farming, tailoring and fishing).

The CV does calculate the extent to which individuals are willing to trade money for improvements in their health status. The CV is derived from welfare theory and also consistent

[31] These estimates are for individual members. The average number of members in a household is five.

with Lancaster's RUT since it calculates the probability of choosing each alternative by incorporating in its estimation the weights of the welfare effects arising from changes in the attributes of a program.

For a policy change say from a public provider to a non-public provider with a decrease in the cost of health insurance and waiting time from 10000SLL to 4000SLL and 90minutes to 45minutes respectively, the CV is 10180.42SLL/$2.3. Across locations, households in urban locations have a higher CV, implying, they are willing to pay a higher amount than their rural counterparts (about 25%) to switch to the best scenario, which supports earlier WTP results. Possible explanation here, as discussed already, is the higher level of awareness amongst these urban households. Among the informal sectors, households in petty trading, "okada" and fishing have higher CV's because they live in urban areas or closer to urban dwellings.

3.4.6 Tests of Validity of Responses

The validity of responses basically ensures that the entire measurement process i.e. the collection of data and its analysis must not only be reliable but also free of systematic and uncontrolled bias that distort the estimated results. Economists classed validity into internal and external validity. Internal validity, which is widely used in the literature, refers to the rigour with which the entire study process is conducted. This takes into consideration issues like study design, the care in conducting interviews and decisions concerning what is and what isn't measured. Two approaches are used in this study to test for internal validity, namely, consistency of preferences and consistency with theoretical predictions.

The first approach, consistency of preferences, is tested by including another pair of choice set in the DCE making the pair of choice sets to be 10. The 10^{th} choice set include levels of attributes such that one alternative had better levels on all attributes from which we would expect a rational household to choose the scheme with better levels of attributes compared to the other scheme.

The second test is the theoretical validity wherein the sign and significance of parameter estimates are examined. To perform this test, we created interaction terms between the attribute cost and a characteristic of the household – income, since interacting cost with income subgroups allows us to test the theoretical validity of our model. Instead of using cost as an attribute, we used the newly created interaction variables, which we use to run the regression and the outputs used to estimate WTP for a reduction in waiting time. We hypothesized that as income increases, households are WTP more for a reduction in waiting time. A random effects logit model is used to estimate our model with the new interaction variables as shown in table 3.11 below.

Table 3.9: Tests of Theoretical Validity

Attributes	Marginal Effects (Standard Errors)	WTP*
Coverage	0.54589 (0.01624)***	
Waiting Time	-0.00793 (0.00071)***	
Public Provider	0.05363 (0.0159)***	
Non-Public Provider	0.564936 (0.01641)***	
Cost_Income1	-0.000044 (3.92e-06)***	181.90
Cost_Income2	-0.000041 (4.56e-06)***	192.50
Cost_Income3	-0.000042 (5.36e-06)***	187.94
Cost_Income4	-0.000041 (8.49e-06)***	195.83

Wald Tests: Income1-Income2=0, p=0.0000; Income1-Income3=0,p=0.0000; Income1-Income4=0,p=0.0000; Income2-Income3=0,p=0.0000; Income2-Income4=0,p=0.0000; Income3-Income4=0,p=0.0000;
*The WTP values are for a reduction in waiting time and are for individual members in a household.

The Wald test is used to test whether the newly constructed interaction variables are statistically different from each other. The z test is also used to test for significant differences in the resulting WTP values obtained by finding the ratio between the marginal effects of waiting time (numerator) and the marginal effects of each of the interaction variables (denominator). A priori, it is expected that as income increases, households are WTP more for a reduction in waiting time.

The results show that income levels are positively and significantly associated with the WTP values for reduction in waiting time. Households on lower income (Cost_Income1) have a lower WTP (909.5SLL/$0.21) and those on higher income (Cost_Income4) have a higher WTP value.[32]

[32] The household WTP value was obtained by multiplying the individual WTP by the average household size (5).

This supports our theory earlier on, that is, as income increases, households are willing to pay more for a reduction in waiting time. The same is also true for the other attributes. The Wald test and z test also confirms that our interaction terms are not only statistically significant but also statistically different from each other which also lends credence to our theoretical validity test.

3.5 DISCUSSION AND CONCLUSION

To the knowledge of the researchers, this is the first study that looks at WTP for health insurance among informal sector workers in a Sub Saharan African country context using the DCE methodology. It also looks at the issue of theoretical validity and whether location matter in deciding a household's WTP for health insurance.

This paper seeks to estimate household's WTP for health insurance among informal sector workers using the DCE. Eight informal sectors are chosen and they include petty trading, subsistence farming, commercial bike riding (Okada), cattle rearing, fishing, tailoring, quarrying, and mining. In several areas of health care, WTP have been estimated for most of the studies within the health economics literature, especially when cost or price is an attribute in the choice experiment. However, only one study (Vroomen and Zweifel, 2011) has looked at WTP for preferences for health insurance in Germany and the Netherlands. However, this study is not a developing country context study, which our work is trying to look at, that is, a developing country context case.

The benefits of using DCEs have been highlighted in the literature ranging from its capacity to estimate WTP for health insurance, the preference for attributes in a given choice set and measuring welfare effects of a policy change (Ryan et al. 2010; Ryan and Gerard 2003; Mangham et al. 2008). WTP has increasingly been applied in health care programs to elicit many policy objectives besides WTP.[33] The ability to estimate how much a household will be able to pay for health insurance has wide scale policy implications. A high WTP indicates that households are more likely willing to choose the alternative/option in question relative to the other option, if however that scheme is offered. Despite these growing advantages of using DCEs, the application of DCEs to estimate WTP especially in developing countries remains low. One possible suggestion as explained by Mangham et al. (2008) is that developing countries are plagued with different cultural and language settings and high illiteracy rates, which renders the use of DCEs almost impossible.

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[33] The literature review of this thesis gives a comprehensive review of the application of DCE to WTP in health economics

Our study reveals that WTP is in line with other studies within developing countries, that is, on average, an individual is willing to pay about $3 for health insurance. This study uses the DCE method to estimate household's WTP for health insurance among eight informal sector activities in Sierra Leone. Our results show that the type of provider and coverage are the most important attributes in determining a households' choice of health insurance scheme. Waiting time to see a medical member of staff and accessing a public provider are considered the least important attributes in determining a households' choice of health insurance scheme. However, the time they will wait to see medical member of staff is not too important to them because getting treatment for their health is of grave concern to them than the time they'll have to wait to see one medical member of staff.

Our study shows that the attributes have a significant impact for all informal sectors except petty trading, mining and quarrying, while waiting time and public choice of provider are not significant. For informal sector activities, our study shows a pattern: coverage is the most important attribute for households in activities predominant in rural settings whereas non-public provider is predominantly significant for urban or near urban settings. The result also shows that the probability of a household choosing a non-public provider is almost twice the probability of choosing a public provider. This just suggests that the public health care system in developing countries, especially in Africa, is in an appalling situation (and possibly highly corrupt). Hence households prefer the non-public system. So policy makers can focus their time to having non-public providers for households, as about 60% of them prefer choosing schemes with preference for such providers.

Our results also show that it does make a difference whether you are located in the rural area or urban area (in line with Vroomen and Zweifel, 2011). Our results also show that households in urban areas have a higher WTP than their rural counterparts. In terms of WTP for improvements in any of the attributes, the study found out that urban households are WTP about 50% more than their rural counterparts for an improvement in coverage. This difference is due to the level of awareness and understanding with regard to health issues among urban households which is higher than among rural counterparts, hence they are able to know which coverage will make them better off. One conclusion in the literature is that, WTP increases with the level of awareness. Urban households are WTP about 2 times as compared to rural households for having a non-public provider and about 3 times WTP more for having a public provider than rural households. In terms of waiting time, households in rural and urban areas are willing to pay for a reduction in waiting time. Overall, households are WTP about 68657SLL/$15.4 (about 20.7% of their average income) for health insurance. We observe from our results, that WTP is higher for urban households than rural households. Urban households are WTP about 32813SLL/$7.5 (about 9.5% of income) more than rural households for health insurance. Possible explanation for this higher WTP for health insurance by urban households is, urban households have a better income, better level of education and higher level of awareness, which in line with the literature all positively point towards a higher WTP. We also found that as household's income increases, they are willing to pay more. Those on higher income are willing to pay more but makes a smaller fraction of the income, whereas, those on lower income are willing to pay less and with a higher percentage of their income.

The study also found out that the probability of a household choosing a non-public type of provider is about twice that of choosing a public type of provider. A rational individual is WTP about 10180SLL/$2.3 for a change in policy from a public provider to a non-public provider, a decrease in cost from 10000SLL to 4000SLL and a reduction in waiting time from 90minutes to 45minutes.

However, this study has some limitations ranging from weakness of DCE to weakness of experimental design. The first, which is a weakness of the DCE method, is that respondents' sometimes experience difficulties when answering the questions. Some of the difficulties encountered as reported by the interviewers used in this study are finding difficulty in remembering their health care expenditure; some just find it difficult to understand the DCE process, hence spending longer than normal times. In addition, disadvantages of face-to-face interviews are that it takes respondent's time, it is costly, being worried about confidentiality of information and interviewer bias may have occurred from the interviewers. Secondly, the experimental design used in this study could have been better. The equal levels of attribute in the DCE design used in this study (i.e. three levels for each attribute), may impose a cost on the experiment because some attributes may naturally require more than three levels (Hensher et al. 2005, pp. 108). The more levels of attributes imply a larger design of this experiment and associated expense and complication and more difficulty in respondents understanding the experiment. A further limitation is related to sampling and non-sampling errors. Sampling error is caused when a sample of a population is observed instead of the whole population. Increasing the sample size and the method used to select the sample can mitigate this type of error. The second, non-sampling error is the most important source of error in estimates. This type of error is independent of sample size. Non-sampling errors may arise from many different sources, such as interviewers may make mistakes in the collection of data due to personal variations. Respondents may also forget activities such as hospital visits or the associated costs and they may respond irrationally. For example, even though respondents were assured of secrecy of information and data and that their information will be erased as soon as this study is completed, some respondents may not want to provide some of their information accurately, such as their income. Fourth, this study only looked at informal sector workers in two (northern and western) out of four regions. Including the other regions would have given a nationalistic picture of the work. Next, the eight informal sectors chosen do not represent all the informal sectors in Sierra Leone. Other sectors were left out in this work. The main reason for this kind of action was lack of finance to include the other sectors. Finally, a pre – survey was carried out in only two areas – Waterloo and Bombali – to determine the attributes and their levels to use. In as much as they are reflective of what is in the literature, the pre – test should have included more communities.

Despite these limitations, the study is important by revealing informal sector households are willing to pay more for a non-public provider than a public provider and for an improvement in coverage. This sends out a clear message to policy makers that in establishing a health insurance scheme, the focus should be on non-public provider and the type of coverage. It is also observed that households in urban areas are in general WTP more than their rural counterparts.

Appendix 3A: Checklist of factors to consider in undertaking and assessing the quality of a DCE

1. Conceptualizing the Choice Process – This involves making decisions with respect to the type of choice to be used and whether to include or not opt out option.
2. Attribute Selection – This involves making decisions relating to the kind and number of attributes to be included; the appropriateness of the coverage; whether or not to include price and risk as attributes.
3. Level Selection – How were the levels derived; was the number per attribute appropriate; and was an appropriate range used.
4. Experimental Design – It involves deciding on the type of design (full or fractional) used; type of effects; what choice sets were arrived at; what are the properties and efficiency of the design; and how many choice sets per respondent were agreed at.
5. Questionnaire Design – This involves designing the questionnaire and including issues like were the research questions answered (dealt with) in the questionnaire and what is the appropriate method of communicating the attributes to be used.
6. Pilot Test – Used to check the comprehension of the attributes and the DCE process to the sample population; check length and timing to complete the questionnaire; and check the usability of the proposed method.
7. Population/Study Perspective – Was the right population selected and was the research question(s) appropriate for the kind of target of population.
8. Sample and Sample Size – This involves the kind of inclusion/exclusion criteria to be used and the appropriateness of the sample size with respect to the model to be estimated.
9. Data Collection – This deals with issues ranging from determining the recruitment method to be used, data collection method, the response rate and incentive used to enhance the response rate.
10. Coding of Data – Was the right coding used to estimate effects?
11. Econometric Analysis – It involves handling issues like goodness of fit; was the right estimation method used taking into consideration experimental design and choice response; was alternative specific constant included; and were socioeconomic and socio - demographics used?
12. Validity – Did the research measure what it intended to measure and what was the level of truthfulness in the measure; was it internal or external validity; and what the reliability of the research.

13. Interpretation – This answers the question as to whether the results were at par with a priori expectations.
14. Welfare and Policy Analysis – This handles the appropriateness of the research with regards to the policy objective at hand; was probability analysis undertaken; and was WTP estimated.

Source: Lancsar and Louviere, 2008

Appendix 3B: Willingness to Pay Estimates per Individual

Attributes	Main Sample	Rural Location	Urban Location
Overall WTP	13546	10774	17237
Coverage	6392.92	5700.01	7313.51
Public Provider	629.55	333.66	1032.06
Contracted Provider	6616	4812.54	9013.37
Waiting Time[34]	92.90	71.89	121.72

[34] Whilst these ratios will result in negative WTP, representing what individuals would need to be compensated for an increase in waiting time, the figures represented show WTP for a reduction in waiting time.

Appendix 3C: Regression Results: Using both Moderate and Comprehensive Coverage

Choice	Coefficients (Standard Error)
Moderate Coverage	-0.24124 (0.0337)***
Comprehensive Coverage	-1.0331 (0.03750)***
Waiting Time	-0.00404 (0.00071)***
Non Public	1.04605 (0.03268)***
Public	0.0525 (0.03239)
Cost	0.00002 (6.14e-06)**
Constant	0.22222 (0.06207)***
No of Observations	26244
Wald chi2	2340.08
Prob.>chi2	0.0000
Log Likelihood	-16873.16

***p<0.01; **p<0.05; *p<0.1

Appendix 3D: Total/Overall WTP using different attribute Packages

Package	Description				WTP (SLL)	% of Average Household Income
	Coverage	Non-Public	Public	Waiting Time (Minutes)		
1	Moderate	Yes	No	30	78965	23.7
2	Moderate	No	Yes	30	49033	14.7
3	Moderate	Yes	No	45	85925	25.8
4	Moderate	No	Yes	45	55993	16.8
5	Moderate	Yes	No	60	92885	27.9
6	Moderate	No	Yes	60	62953	18.9

As you can see from the Table above showing various packages of WTP for households, the figures ranges from about 15% of income to about one-fourth of income. This is a high proportion of income, which also explains our findings in chapter five (5) on Ability to Pay. As evidenced in chapter five (5), households are WTP for health insurance, but lack the ability to pay for it.

Appendix 3E: Regression Results by Income Groups

Attributes	Income One	Income Two	Income Three	Income Four
	Coefficient (SE)	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
Coverage[1]	0.46218	0.61116	0.59434	0.49872
	(0.02591)***	(0.02482)***	(0.04223)***	(0.06602)***
Waiting Time	-0.00698	-0.0087	-0.00939	-0.00121
	(0.00113)***	(0.00108)***	(0.00184)***	(0.00285)
Non Public	0.83411	1.42279	1.16605	0.95991
	(0.05195)***	(0.05064)***	(0.08561)***	(0.06438)***
Public	-0.07766	0.22502	0.27598	0.27001
	(0.0511)	(0.04815)***	(0.08268)***	(0.06494)***
Cost	-0.00008	-0.00009	-0.00009	-0.00007
	(8.53e-06)***	(8.10e-06)***	(0.00001)***	(0.00002)***
Constant	0.30080	0.21344	0.2046	0.35392
	(0.09937)***	(0.12255)*	(0.06385)***	(0.10387)***
Mean Income (SLL)	171284.40	298500	415633	556185
No of Observations	3924	11736	9054	2412
Wald chi2	399.89	1411.34	693.81	158.02
Prob.>chi2	0.0000	0.0000	0.0000	0.0000
Log Likelihood	-2485.34	-7283.33	-5888.78	-1584.32

***p<0.01; **p<0.05; *p<0.1; 1. Moderate coverage is used to define coverage

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Chapter 4 – Impact of Corruption on Households' Participation in Health Insurance

4.1 INTRODUCTION

One of the fundamental problems facing developing countries is the manner in which they have been ravaged by corruption (Mostert et al., 2012). The health systems in these countries are inefficient, have poor quality services, inequitable access and inadequate funding. The health care services are limited and expensive, hence the poor cannot access them and often forgo or delay necessary care due to their inability to pay the huge out of pocket (OOP) payments. Lack of access to health care, high health expenditures and corruption are raised in the literature as primary causes of poverty and deprivation among rural households in poor countries. Those seriously affected in this crisis are workers in the informal economy who face clear and distinct threats to their human security.

Public goods are characterized by market failures, which warrant government intervention through public provision, financing and the regulation of such services. However, corruption is seen as a by-product of government intervention that can negatively affect the provision of health care services (Acemoglu and Verdier, 2000; Agbenorku, 2012).

Considerable evidence supports the point that unofficial payments are deeply entrenched in markets for health care in developing and poor countries. Studies also show that corruption within the health sector contributes significantly to the poor health situation in developing countries. Over 80% of the world's population live in developing countries and are faced with increasing levels of corruption (Mostert et al., 2012). Corruption in the health sector can have severe consequences for access, quality, equity and the effectiveness of health care services (DFID, 2010). Klitgaard et al. (2000) define corruption as the abuse of office for personal gain. A study of 71 countries by the World Bank (1997) has revealed that highly corrupt countries (i.e. with high corruption indices) have higher infant mortality rates, even after adjustments for income, female education, health expenditure and urbanization. Corruption in the health sector is seen as a pervasive and corrosive problem. Vian (2007) concluded that at the micro level, there is mounting evidence of the negative effects of corruption on the health and welfare of citizens.

A study by the World Bank (2010) on child death caused by malaria in rural Tanzania concluded that 80% of these cases went to modern health facilities but, to a large extent, were not cured due to corrupt practices such as drug pilfering, provider absenteeism, stolen equipment and very little diagnostic effort.

The study of the impact of corruption in the health sector is important because: (1) the large amount spent on health at both the global and national levels creates a breeding ground for abuse and illegal gain; (2) the causes of market failure in the health system create opportunities for corruption, and (3) monitoring and accountability proves to be difficult as there are several actors with subsequent issues of information asymmetry (Vian, 2007).

Sierra Leone is not an exception to this problem. Corruption is one of the most important factors to have retarded growth in the health sector. Corruption in Sierra Leone's health sector ranges from demanding bribes for use of basic services to large-scale misuse of public goods for private gain by public officials (DfID, 2013). The 2012 World Bank control of corruption index placed Sierra Leone in the bottom 25%, and in the Transparency International (TI) Corruption Perceptions Index (CPI) of 2013, Sierra Leone scored 30 out of 100 (where 0 is considered highly corrupt and 100 very clean) and ranked 119 out of 175 countries. A local survey by the Anti-Corruption Commission (ACC) in Sierra Leone (2010) shows that the majority of Sierra Leoneans have experienced corruption in one way or the other, with 94% classifying it as a problem. In March 2013 the ACC indicted 29 officials of the National Health Sector Support Project (NHSSP) at the Ministry of Health and Sanitation for various corruption offences regarding misuse of the Global Alliance for Vaccines and Immunization (GAVI) funds. The various charges amounted to $2,436,921.07.[35]

We can observe from most studies that corruption within the health sector is serious and that something needs to be done urgently to solve it, or else the poor will continue to get poorer and their life expectancy shorter. However, before coming to this conclusion, the magnitude of the impact of corruption needs to be looked at. This is where the contribution of this chapter lies.

Although corruption does occur in developed countries, as explained in the TI report (2006), there is usually full access to medical services. However, in developing countries, access to medical facilities is restricted to those who can afford it. The focus of this chapter therefore is twofold: first, to look at the relationship between perceived and actual corruption on one hand and household characteristics on the other, and secondly to look at the impact of corruption on households' participation in a health insurance scheme. As corruption has a negative impact on a household's decision to participate in a health insurance scheme, the key questions that this

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[35] Culled from the ACC website www.anticorruption.gov.sl on 12/11/2013.

research tries to answer are: (1) What is the relationship between the types of corruption and household characteristics? (2) Are there fundamental differences between the two measures of corruption? (3) How severe is the magnitude of the impact? In trying to unravel this problem, the paper is structured as follows: First, it looks at some background literature on corruption, and outlines the methodology used. This is followed by the econometric specification and an analysis of the results. The final section discusses the results.

4.2 REVIEW OF THE LITERATURE

Several definitions of corruption are used in the literature – Klitgaard et al. (2000), Alatas (1986), and Transparency International (TI). While Klitgaard et al. (2000) define corruption as the abuse of office for personal gain; Alatas (1986) defines it as the abuse of trust and the intentional violation of duty, motivated by gaining personal advantage, towards a party in need of a decision or service by a public servant. TI on the other hand defines corruption in the health sector as the abuse of entrusted power for private gain, in the form of bribery (for instance, doctors demanding pregnant women to pay consultation fees when they are not supposed to), extortion (e.g. the use of hospital funds for private use), manipulation of information in drug trials, overbilling, mis-procurement, diversion of medicines and supplies, and nepotism (employment of family members and friends irrespective of their inability to perform well in the job).

Corruption is a hindrance to society. The TI report of 2006 highlights that; corruption is common where large sums of money flow, the health sector being a good example. The report further states that the stakes are high and resources precious: money lost to corruption could have been used to buy medicines, equip hospitals or employ health care staff. There are seven processes with a high inherent risk of corruption, namely: provision of services by medical personnel; human resource procurement; drug selection and use; procurement of drugs and medical equipment; distribution and storage of drugs; regulatory systems, and budgeting and pricing (The Anti-Corruption Resource, 2008).

Corruption in the health sector can be seen as a matter of life and death. As explained by TI (2006), it is a syndicated business and the key players are health care central authorities/administrators, medical suppliers/contractors, and health care providers. The 2006 Global Corruption report focusing on corruption in the health sector concludes that corruption in the health sector is a global problem that is complex and deadly.

The TI (2006) report highlighted three major reasons why the health sector is vulnerable to corruption: (1) the problem of information asymmetry in the health sector (Vian 2007); (2) the high level of uncertainty in health outcomes or demand for health services – issues such as who will fall ill, when, and what will they need (Savedoff, 2006); and (3) the complexity and opaqueness of health systems. The health sector in any country is among the sectors with the highest number of staff and expenditure. This large number of policy makers, suppliers and health professionals complicates the generation and analysis of information, transparency, and the detection and prevention of corruption.

Health officials engage in corruption for various reasons, but the key conditions for corruption, as discussed by Vian (2007) are: (1) officials must have opportunities like monopoly of services, discretion to make decisions, poor accountability and transparency in order for them to engage in corruption; (2) a conducive environment must be created by social norms, individual beliefs and the eroding of public service values to ensure corruption thrives well; and (3) low salaries, personal financial debt and similar pressures force public officials to engage in corruption.

To a greater extent, the type of health financing system determines the level of corruption within a health system. A health financing system will be more vulnerable to corruption in procurement and abuses that undermine the quality of services than other financing systems (U4 Anti-Corruption Resource Centre, 2008). For instance, if a system of finance relies heavily on billing insurance companies directly (known in the literature as an integrated financing system) it is more vulnerable to funds being diverted by inducing treatment not required medically; similarly, in a finance/provider system there is a risk of the central health care authority being billed for services not provided. Integrated health systems are common in developing countries. Table 4.1 below presents the various health financing methods and their associated characteristics and risks

Table 4.1: Health financing and risks of corruption

Method of Financing	Characteristics	Corruption risk
Taxes	Normally associated with free or almost free service deliveries. Limitations: Raising taxes in low-income countries is problematic. Rich people also get a disproportionately high share of public subsidies	Large-scale diversions of public funds at ministerial level. High risk of informal or illegal payments. Corruption in procurement. Abuses that undermine the quality of services.
Social Insurance	Social insurance compulsory. Premiums and benefits described in social contracts (laws or regulations). Limitations: Not every citizen eligible for coverage and benefits. Only applicable for formal employees.	Most common abuses include excessive medical treatment, fraud in billing, and diverting funds.
Private Insurance	Buyer voluntarily purchases insurance (on an individual or group basis).	Same as for social insurance schemes.
Out-of-Pocket (OOP) Payments	Patients pay providers directly out of their own pockets for goods and services. Limitations: Costs are not reimbursable.	With weak regulatory capacity, there is a high risk of over-charging and inappropriate prescribing of services. Also a risk of employees pocketing official fees collected from patients. No guarantee that all health services are of value to those buying them.
Community Financing	Community members pay in advance ("pre-paying"). Under most community-financing schemes, the financing and delivery of care are integrated.	Problems are similar to the tax system, except that the provider is directly responsible to the community, thus reducing risk of corruption.

Source: Savedoff, 2003 in U4, 2008.

In the health sector, the effect of corruption is vivid and ranges from unavailability of medicines to lack of health care personnel, and even death. In as much as the effect of corruption in the health sector is clear, however, the overall cost of this corruption is difficult to determine because of numerous problems including: the diversity of health systems globally; the difficulty of distinguishing between corruption, inefficiency and honest mistakes, the paucity of good record keeping in many countries, and the range of stakeholders in this sector. All these make determining the cost of corruption in the health sector cumbersome.

In developing countries, corruption affects all aspects of society including the health sector –

mainly public hospitals are affected here. Even though corruption is present in every sector in developing countries, the key question is why is it rife in the health sector? In the health sector, corruption is hatched in the uncertainty of demand, and spreads to various other sub-sectors within the health system, thereby affecting almost all health care participants and stakeholders and hence creating expectations of bribes.

Lewis (2007) explained that in developing countries medical staffs are involved in under-the-table corruption because of the low and irregular payment of their salaries and lack of government action in the health care system. She further states that this low pay serves as an incentive for patients to provide under-the-table payments, the other reason being the culture of giving gifts.

Olken and Pande (2011) argued that even though corruption is substantial in magnitude, it does not necessarily answer the question of whether it actually has a negative impact on economic activity. They further explain that the impact of corruption depends on whether the corrupt act can lead to an economic efficiency loss (or gain), which also depends on whether the deadweight loss from the bribes collected are greater (or smaller) than the equivalent deadweight loss from taxation needed to raise revenue to pay the equivalent amount of money in salaries were corruption eliminated.

The effect of corruption on the poor is immense, as they do not have the money needed to pay bribes or seek private alternatives. The vulnerability of the poor is better understood in terms of powerlessness as both power and powerlessness determine access to aid (TI, 2006; Einterz, 2001; Dyer, 2006). The powerless and poor alike cannot safeguard their rights and are hence neglected and excluded by health care providers. A key conclusion in the World Bank study of 1997 is that countries where corruption is higher tend to have a higher infant mortality rate (IMR) and by extension a higher maternal mortality rate (MMR), and this is supported by other studies in the literature (TI, 2006; Einterz 2001; Dyer, 2006). The Studies on the effect of corruption on the poor in developing countries concluded the following: first, that corruption deprives patients of access to medical care due to the increased cost of health care resulting from many unofficial payment mechanisms – hence the higher OOP payments in these countries; second, it decreases the volume of publicly provided services due to the theft of medicines, which leaves the hospitals/health centres short of supplies; third, it lowers the quality of care due to inadequate treatment and lack of drugs (CIET, 1996).[36] The Public Affairs Centre (PAC) survey revealed that as much as 38% of total hospital expenses borne by households are in the form of bribes, and some 17% of households claim to have made unofficial payments to public hospitals (Paul, 1998 in Gupta et al., 2000).[37] A study by Gray-Molina et al. (1999) also revealed that people's perception of corruption in the health sector strongly correlates with input overpricing and unofficial payments.

4.3 METHODOLOGY

4.3.1 Study Area and Sampling

This study is carried out in Sierra Leone – a country of about 6 million people living along the west coast of Africa. The study uses data from a DCE conducted in the northern and western regions of Sierra Leone. We use these regions in our study because as Deaton and Paxson (1997) explain, the choice of a study area when purposively driven by a researcher's prior knowledge and familiarity, enhances the accuracy of the data to be obtained at least to a certain degree, and the econometric estimates obtained from it.

Statistics Sierra Leone (SSL) design the sample needs and locations for this study based on recent pre-census data that has information on settlement names, population and household sizes. A two-stage stratified random sampling method is use to identify the households. The first stage involve dividing the population into regions/districts, while the second stage involve the process of dividing the population into rural and urban areas in each district. The purpose is to ensure a representative sample of informal sector households in both villages (rural areas) and major towns (urban areas). The household is the economic unit we use in this study and we randomly chose households from both strata. The choice of the household as the economic unit stems from the notion that in poor informal households, the economic decision to purchase health care among these rural and mostly farming households is more likely to be a household rather than an individual decision.

4.3.2 The Discrete Choice Experiment (DCE) Design and Attributes

We use the DCE method to collect our data.[38] The DCE is an attribute-based measure of benefit/value (Ryan and Gerard, 2003a), and its appropriateness is based on two premises: first,

[36] CIET (Community Information, Empowerment, and Transparency International) is an international organization that conducts surveys on public service delivery.
[37] PAC is a local agency in Bangalore, India that conducts public service delivery surveys
[38] See Chapter 2 for a detailed explanation of the DCE method.

goods/services can be described in terms of their attributes, and second, the extent to which an individual values a good/service depends on the characteristics of these attributes (Ryan, 2004). This survey-based data collection method is used to establish preferences for a health insurance scheme by allowing households to choose to participate, or not to participate, in either health insurance scheme A or health insurance scheme B, described by their attributes and attribute levels. At least one attribute of the alternatives varied systematically by allowing information relating to trade-offs between attributes to be inferred. The DCE method therefore looks at the importance of each attribute in the introduction of a health policy, say a health insurance scheme, allows the estimation of welfare when attribute levels change, and permits the estimation of willingness to pay (WTP).

A total of 50 households took part in the pre-test survey.[39] Analysing the responses, and in accordance with related literature, we chose the following attributes: cost, coverage, waiting time and choice of provider. We base the choice of attributes on relevance to policy and feasibility of administration, considering that the survey consists of personal interviews carried out by us at the homes of the population we chose. These attributes are also widely used in the literature.

Prior to agreeing to the number of levels to use for each profile, we take into consideration recommendations from experts and policy makers, and the current health situation and poverty profile of Sierra Leone. From these, we assign three levels to each attribute. The attributes and their levels are shown in table 4.2 below.

[39] See Chapter 3 on how the DCE process was carried out.

Table 4.2: Attributes and Levels used in the DCE[40]

Attributes	Attribute Levels	Description
Coverage	Simple Moderate Comprehensive	Outpatient treatment of minor diseases Doing minor operations and Inpatient treatment of minor diseases Major operations and inpatient treatment of diseases
Waiting Time	45 Minutes 60 Minutes 90 Minutes	The length of time one has to wait before seeing a medical personnel
Choice of Provider	Private Public Non-Public	Health centres and hospitals owned and operated by private people Health centres and hospitals owned and operated by Government Health centres and hospitals owned and operated by religious and other groups, i.e. not owned by government
Cost/Premium	4000SLL 6000SLL 10000SLL	The monthly premium a member will pay for the scheme

1. SLL stands for Sierra Leonean Leone, the local currency.

The four attributes with three levels each results in a full factorial design with 81 possible combinations. The total of 81 possible health insurance schemes to be generated is quite a large number and would have posed a high cognitive burden on respondents. We therefore use a fractional factorial design to reduce the choice sets to a manageable number. We use the software SPSS to generate a DCE design that results in 18 choice profiles which are subsequently reduced into two blocks of nine choice sets each. The total number of choice sets we used in the experiment is nine, which is within the acceptable range for DCE studies (de Bekker- Grob et al., 2012). However, we include a tenth choice set to test respondents' understanding of the DCE method.

We develop an additional questionnaire to collect information on the socio-demographic characteristics of households and their current health and health financing methods.

This study used the choice format employed by Vujicic et al. (2010b) and Pedersen et al. (2012), estimating two binary discrete choice questions – first, the household is asked which of the two health insurance schemes, A or B, they preferred, and second, whether they would participate in

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[40] See chapter three of this thesis of definition of each of these attribute levels as used in the study

the scheme they chose over their current health financing method. We used this method to estimate the impact of corruption on households' participation in these schemes. This method estimates the probabilities of participation/take-up and non- participation. An example of the choice format as presented in the survey is shown in table 4.3 below.

Table 4.3: An Example of the Choice Format Presented in the Survey[41]

Question 3	Scheme A	Scheme B
Coverage	Comprehensive	Simple
Waiting Time (Minutes)	45	90
Choice of Provider	Public	Contracted
Cost (SLL)	4000	6000
Which Scheme would you prefer?		
Would you participate in the chosen scheme?	Yes	No

Table 4.3 shows that the study used an opt-out option for the DCE. This gave respondents the option to choose not to participate in any of the health insurance schemes; as for some households non-participation was a preferred choice.

4.3.3 Data Collection

This study used an interviewer-administered questionnaire. We recruit and train interviewers on how to administer a DCE survey. Next, we train interviewers on two key issues: first, what the DCE is and what it is all about; and second, how to conduct a DCE survey.

We chose eight informal sector activities for the survey: petty trading, subsistence farming, commercial bike riding (Okada), cattle rearing, fishing, tailoring, mining and quarrying. We chose these sectors because they are the most predominant informal sector activities in Sierra Leone. A total of 1670 households took part in the survey. Since this study makes use of an MXL model, a larger sample size is preferred, as a larger sample size can resolve the insufficient variation to model the kind of distributional information required in an MXL model. Chang and Lusk (2001) explain this point clearly:

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[41] Contracted choice of provider is replaced with non-public provider to give a better understanding to the reading. Therefore, contracted provider is changed to non-public provider hence forth in this chapter.

> When the sample size increases to N = 1000, the MXL estimates more closely approximate the true values. While the mean estimates across the 500 iterations converge to the true values for the parameter means (β_1 and β_2), the mean estimate for δ_2 remains about 10% below the true value of 1. The results suggest that when the sample size is small (for e.g., with data from economic experiments), there may be insufficient variation to model the kind of distributional information being assumed by the MXL. People may be asking "too much" of their data when trying to fit an MXL model to small- sized datasets. Nevertheless, results suggest that increasing the sample size solves some of the problems. (Chang and Lusk, 2011, pp. 171)

To test the questionnaire, a pilot study is conducted among informal sector households in the rural western area and Bombali district. This pilot work provided feedback on households' interpretation of the attributes of the health insurance schemes, the time a household takes to complete the questionnaire and the acceptability of the nine choices within the DCE. Based on feedback from the pilot survey, we made some adjustments before administering the main questionnaire.

The data is double entered into excel by a team of data entry staff and checked for consistency. After the inconsistent data is removed, the final data is transferred into STATA for further analysis. A total of 1458 households' data is used for the final analysis. As the experimental design produced nine choice sets with three alternatives that 1458 households had to choose from, a total of 39,366 observations are produced for the analysis.

4.3.4 Variables Used

The decision regarding the kind of variables to use in the model is a very important and crucial stage in the work and it goes a long way towards determining how accurate the results will be. Two sets of variables are used in this study: choice attributes and household characteristics. As the survey instrument include questions on the socio-demographic characteristics of the household, perceptions of corruption and payment of bribes and other issues, we collect information on households' demographic and corruption issues in the health sector. The other information we capture is households' main source of treatment when a member is sick, giving seven options: self-treatment, traditional treatment, health centre, hospital, treatment through drug peddlers, the pharmacy and no treatment whatsoever.

The DCE attributes (cost of scheme, coverage, waiting time, and choice of provider) and the levels we used are shown in Table 4.2 above, and an example of the type of choice question asked is shown in table 4.3 above. The attributes are used to estimate the impact of corruption on participation in health insurance.

Two measures of corruption are used in this survey. First, we ask households to show how they perceived corruption within the health sector. They are to answer on a scale of 1 (not corrupt) to 4 (highly corrupt). The second very important measure of corruption used is whether households pay for treatments considered free for the following: children under five years old, pregnant women and lactating mothers. This variable is used because in April 2010, the government of Sierra Leone introduced free health care treatment for people in these categories. These services are free at public hospitals or health centres but not in private or non – public hospital and health centres. What we draw from the survey is if households answer they do pay for these treatments and services, which are supposed to be free, there is an element of corruption. According to the literature, this is known as actual corruption (Olken, 2009). Another issue also addressed by the study is why households normally pay for health services that are supposed to be free. The reasons given by households are: they are unaware these services were free, the medical personnel requested the payment, they pay willingly, and other, less important, reasons.

Other characteristics of the household used are as follows: households per capita income;[42] education; location of the household – rural or urban; distance to the nearest health centre; age of the head of household; whether any member of the household suffered from malaria or typhoid;[43] and whether the household received remittance.

The choice attributes vary with every choice made by the household whereas the household characteristics do not vary with choice. As all the variables – dependent and explanatory – to be used must vary with choice, it is almost impossible to use household characteristics in such a model. In the MXL model, as the socio-demographic characteristics of the household do not vary with choice as stated above, they cannot enter directly into the model. An ingenious way to include such variables into our model is to interact them with the attributes of the health insurance scheme to enable slope coefficients to differ between sub-groups and to preserve the variability in attribute–level distribution. In addition, Hensher et al. (2005) explain that matching the attribute and the socio-demographic characteristics of the household is important as it preserves the variability in the attribute–level distribution. As we want to establish the impact of each type of corruption on participation in health insurance, we form two new interaction variables (fhccorr_public and corrperc_public) as defined in Table 4.4 below. The two new interaction variables we form vary according to choice and household characteristics. Table 4.4 presents the variables used in our analysis and their definitions.

[42] We constructed the household per capita income, i.e. the household's income per member or per head.
[43] We used malaria and typhoid fever because at the time of the survey, they were the two most deadly diseases in Sierra Leone.

Table 4.4: Variable Definitions

Variable	Definition
Participation	Reported household's decision to participate in health insurance; = 1 when answered Yes to participation and 0 otherwise.
FHC Corruption	When the household reports that they pay medical expenses for a member in any of these categories: under-fives, pregnant women, and lactating mothers; = 1 when answered Yes and 0 otherwise
Corruption Perception	The household's perception of corruption in the health sector (1) Not corrupt (2) Fairly corrupt (3) Corrupt (4) Very corrupt.
Cost	Attribute that defines the amount to be paid for the health insurance scheme: 4,000, 6,000 & 10,000 SLL.
Coverage[1]	Attribute that defines the benefit of the scheme: Simple, Moderate & Comprehensive.
Waiting Time	Attribute that shows the waiting time to see a doctor/nurse: 45, 60 and 90 minutes.
Public Provider	Attribute that shows one of the type of providers a member of the scheme can visit; = 1 when visited and 0 otherwise.
Contracted/Non - Provider	Attribute that shows a type of provider a member of the scheme can visit; = 1 when visited and 0 otherwise.
Household Per Capita Income (PCI)	Calculated household per capita income in Sierra Leonean Leones (SLL) derived by dividing household income by household size.
Petty Trading	Reported type of informal sector = 1; 0 otherwise.
Subsistence Farming	Reported type of informal sector = 1; 0 otherwise.
'Okada'	Reported type of informal sector = 1; 0 otherwise.
Cattle Rearing	Reported type of informal sector = 1; 0 otherwise.
Fishing	Reported type of informal sector = 1; 0 otherwise.
Tailoring	Reported type of informal sector = 1; 0 otherwise.
Mining	Reported type of informal sector = 1; 0 otherwise.
Quarrying	Reported type of informal sector = 1; 0 otherwise.
School	Reported whether household went to school = 1; 0 otherwise.
Distance to HC	Reported distance in miles from village to nearest health centre.
Age of Household Head	Reported age of head of household.
Shock	Reported shock to household's main informal economic activity = 1; 0 otherwise.
Household Size	Number of members in the household at the time of the interview.
Diseases	Whether any household member has suffered from malaria or typhoid fever in the three months prior to interview; yes = 1; 0 otherwise
Location	Household location – rural or urban; Urban = 1, Urban = 0.
Remittance	Whether household receives remittance; Yes = 1, 0 otherwise
News	Whether household head listens to radio or read newspapers; Yes = 1; 0 otherwise
FHCCorr_Public	An interaction term of the impact of FHC corruption on participation in a health insurance scheme that provides services through a public choice of provider; Yes = 1; 0 otherwise.
CorrPerc_Public	An interaction term of the impact of households' perception of corruption on participation in a health insurance scheme that provides services through a public choice of provider; Yes = 1; 0 otherwise

1. Moderate coverage is used as the definition of coverage in this work.

4.3.5 Data Summary and Descriptive Statistics

Table 4.5 below presents summary statistics for the attributes of the scheme and households' socio-demographic characteristics. The summary statistics are based on the main sample, type of corruption, free health care corruption and households' perception of corruption in the health sector.

Table 4.5: Summary Statistics

	Main Sample (N = 39366)		Yes to Free Health Care Corruption (N = 17226)		Perceived Corruption Highly in Health Sector (N = 24920)	
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Corruption Perception	1.88129	1.00496	1.83061	0.88147	2.55361	0.49713
FHC Corruption	0.43759	0.49610	1	0	0.41709	0.49308
Attributes						
Cost	4444.44	3745.0	4444.44	3745.06	4444.46	3745.11
Coverage	0.22222	0.41577	0.22222	0.41577	0.22243	0.41573
Waiting Time	43.44	34.24	43.32	34.23	43.33	34.23
Public Provider	0.22222	0.41577	0.22571	0.41598	0.22243	0.41589
Non Public Provider	0.22222	0.41577	0.22222	0.41575	0.22219	0.41573
Informal Sector						
Petty Trading	0.26955	0.44373	0.24922	0.43257	0.24699	0.43127
Sub. Farming	0.19761	0.39820	0.24469	0.42991	0.22753	0.41924
‘Okada’	0.22420	0.41706	0.20516	0.40383	0.21453	0.41050
Cattle Rearing	0.04938	0.21667	0.05799	0.23374	0.04876	0.21536
Fishing	0.07819	0.26847	0.06113	0.23957	0.08668	0.28137
Tailoring	0.10494	0.30648	0.11285	0.31642	0.11810	0.32273
Mining	0.03704	0.18886	0.03605	0.18642	0.03467	0.18295
Quarrying	0.03909	0.19382	0.03292	0.17842	0.02275	0.14912
Per Capita Income (SLL)	77544.7	38228.3	73416.77	35747.15	74600.77	36137.91
School	0.67497	0.46839	0.62557	0.48399	0.69771	0.45926
Distance to HC (Miles)	2.14280	2.59267	2.12320	2.46791	1.91492	2.22153
Age	43.53	13.25	44.62	14.57	44.21	12.57
Urban	0.47531	0.49940	0.44828	0.49733	0.44635	0.49712
Remittance	0.16598	0.37207	0.21473	0.41065	0.17444	0.37949
Diseases	0.73449	0.44161	0.74591	0.43536	0.76164	0.42609
News	0.81073	0.39173	0.85597	0.35113	0.83856	0.36794
Type of Treatment						
Self	0.02675	0.16135	0.01881	0.13585	0.02167	0.14560
Traditional	0.02538	0.15727	0.02665	0.16105	0.02492	0.15588
H. Centre	0.48826	0.49987	0.40578	0.49106	0.55690	0.49676
Hospital	0.24691	0.43122	0.31661	0.46517	0.19282	0.39452
Drug Peddlers	0.08093	0.27274	0.07837	0.26876	0.08668	0.28137
Pharmacy	0.13108	0.33749	0.15221	0.35924	0.11701	0.32144
None	0	0	0.00157	0.03956	0	0
Why Pay for FHC						
Unaware	0.16463	0.37086	0.37612	0.48442	0.149956	0.35665
Request to Pay	0.22795	0.41893	0.51887	0.49966	0.21236	0.40899
Willingly	0.02609	0.15940	0.05962	0.23679	0.03146	0.17456
Others	0.01981	0.13936	0.04528	0.20792	0.02372	0.15217

As Table 4.5 shows, about 52% and 48% of households are located in rural and urban areas respectively. As expected, we see that on average households’ perception of corruption

(corruption perception) is higher for households who perceived corruption highly in the health sector than in the main sample. On average, households' per capita income (PCI) is higher in the main sample than in those households who perceived corruption highly and those who answered yes to free health care (FHC) corruption. The mean for informal sectors is higher for the main sample as compared to the sub-samples except for subsistence farming, cattle rearing and fishing.

In order to provide an in-depth analysis of the sample means, tables 4.6 and 4.7 below give a detailed analysis of the sample base on the type of corruption.

Table 4.6: Sample Means by FHC Corruption[1]

Variables	Yes Free Health Care (FHC) Corruption	No free health care (FHC) Corruption	Difference	Standard Error
Corruption Perception	1.83061	1.92073	-0.09013	0.0102***
Free Health Care Corruption	1	0	1	.
Attributes				
Cost	4444.44	4444.44	1.35e-13	38.04848
Coverage	0.22222	0.22222	2.19e-17	0.00422
Waiting Time	43.32	43.34146	-0.01858	0.34785
Public Provider	0.22571	0.22195	0.00062	0.00422
Non-Public Provider	0.22222	0.22222	2.19e-17	0.00422
Informal Sector				
Petty Trading	0.24922	0.28537	-0.03615	0.0045***
Subsistence Farming	0.24469	0.16098	0.08371	0.00402***
‘Okada’	0.20516	0.23902	-0.03387	0.00423***
Cattle Rearing	0.05799	0.04268	0.01531	0.0022***
Fishing	0.06113	0.09146	-0.03033	0.00273***
Tailoring	0.11285	0.09878	0.01407	0.00311***
Mining	0.03605	0.03780	-0.00175	0.00192
Quarrying	0.03292	0.04390	-0.01099	0.00197***
Per Capita Income (SLL[2])	73416.77	807756.47	-7339.7	386.63***
School	0.62557	0.71341	-0.08785	0.00474***
Distance to HC (Miles)	2.12320	2.15805	-0.03485	0.02634
Age	44.62	42.69	1.92647	0.13428***
Urban	0.44828	0.49634	-0.04807	0.00507***
Remittance	0.21473	0.72561	0.08668	0.00375***
Diseases	0.74591	0.12805	0.0203	0.00449***
News	0.85597	0.77552	0.08045	0.00396***
Type of Treatment				
Self	0.01881	0.03293	-0.01412	0.00164***
Traditional	0.02665	0.02439	0.00226	0.0016***
H. Centre	0.40578	0.55244	-0.14666	0.00502***
Hospital	0.31661	0.19268	0.12393	0.00435***
Drug Peddlers	0.07837	0.08293	-0.00456	0.00277***
Pharmacy	0.15221	0.11463	0.03758	0.00342***
None	0.00157	0	0.00157	0.00027***
Why Pay for FHC				
Unaware	0.37602	0	0.37602	0.00326***
Request to Pay	0.51887	0	0.51887	0.00336***
Willingly	0.05962	0	0.05962	0.00159***
Others	0.04528	0	0.04528	0.0014***

1. Refers to whether the household actually paid for any member in the following category: child under five years old, pregnant woman, lactating mother.
***p<0.01; **p<0.05; *p<0.1;

From Table 4.6 we can see that the mean differences, between households who answer Yes to

FHC corruption and those who did not, vary in most cases and are statistically significant. Due to our large sample, there are statistically significant differences between households who answer Yes to FHC corruption and those whose answers are No, except for the attributes of the health insurance scheme, mining sector and distance to health centre. Households who answered Yes to FHC corruption on average are mainly involved in subsistence farming, cattle rearing and tailoring informal sector activities. They are also on average older, suffering frequently from malaria and typhoid, listen to the news more frequently, and they prefer the following treatments when sick: traditional, hospital, pharmacy and none.

Table 4.7 below presents sample means by households' perception of corruption in the health sector. The mean differences between households who perceive the health sector to be highly corrupted and those who do not are statistically significant, except for the attributes of the health insurance scheme and traditional types of treatment.

Table 4.7: Sample Means by Households' Perception of Corruption in the Health Sector[1]

Variables	Perceived Corruption Highly	Perceive Corruption Less	Difference	Standard Error
Corruption Perception	2.55361	0.72151	1.83210	0.00502***
Free Health Care Corruption	0.41709	0.47293	-0.05584	0.00518***
Attributes				
Cost	4444.46	4444.44	0.0486	39.16251
Coverage	0.22219	0.22222	-0.00009	0.00435
Waiting Time	43.33	43.34	-0.01823	0.35804
Public Provider	0.22243	0.22195	0.00057	0.00435
Non-Public Provider	0.22219	0.22222	-0.00009	0.00435
Informal Sector				
Petty Trading	0.24699	0.30846	-0.06147	0.00463***
Subsistence Farming	0.22753	0.14599	0.08154	0.00414***
'Okada'	0.21453	0.24090	-0.02637	0.00436***
Cattle Rearing	0.04876	0.05046	-0.00171	0.00227***
Fishing	0.08668	0.06355	0.02313	0.00281***
Tailoring	0.11810	0.08224	0.03586	0.0032***
Mining	0.03467	0.04112	-0.00645	0.00197***
Quarrying	0.02275	0.06729	-0.04453	0.00201***
Per Capita Income (SLL)	74600.77	82623.18	-8022.411	397.7135***
School	0.69771	0.63575	0.06197	0.00489***
Distance to HC (Miles)	1.91492	2.53590	-0.62097	0.0269***
Age	44.21	42.37	1.83896	0.13827***
Urban	0.44635	0.52527	-0.07892	0.00521***
Remittance	0.17444	0.68766	0.02305	0.00389***
Diseases	0.76164	0.15139	0.07397	0.0046***
News	0.83856	0.76270	0.07586	0.00408***
Type of Treatment				
Self	0.02167	0.03551	-0.01384	0.00169***
Traditional	0.02492	0.02617	-0.00125	0.00164
H. Centre	0.55690	0.36986	0.18704	0.00514***
Hospital	0.19282	0.34023	-0.14742	0.00445***
Drug Peddlers	0.08668	0.07102	0.01565	0.00285***
Pharmacy	0.11701	0.15534	-0.03832	0.00352***
None	0	0.00187	-0.00187	0.00027***
Why Pay for FHC				
Unaware	0.149956	0.19064	-0.04108	0.00387***
Request to Pay	0.21236	0.25239	-0.04003	0.00438***
Willingly	0.03146	0.01682	0.01434	0.00167***
Others	0.02372	0.01308	0.01064	0.00146***

1. The four options on households' perception of corruption were collapsed into two: first, those who perceive corruption highly are households who chose the options corrupt or very corrupt, that is options1 or 2. Second, those who perceived there to be less or no are those who chose the options not corrupt or less corrupt, that is, options 3 or 4.
***p<0.01; **p<0.05; *p<0.1.

From Table 4.7 we can see that households who perceive corruption to be high in the health sector are mainly in subsistence farming, fishing and tailoring. These households are on average better educated, older, majority receive more remittance, suffer from malaria and typhoid, and listen more frequently to the news. They also prefer a health centre and drug peddlers as their source of treatment when sick. If we observe both sample mean comparisons (Tables 4.6 & 4.7), we realize that households who either perceive corruption highly in the health sector or those who answer Yes to FHC corruption, have similar characteristics, that is, they are better educated, older, suffer from malaria or typhoid, and are involved in subsistence farming and tailoring activities etc.

Table 4.8 below presents the socio-demographic characteristics of households who answered Yes to FHC corruption and those who perceive corruption highly in the health sector.

Table 4.8: Descriptive Statistics

Variables	**Description**	**Main Sample**	**Yes FHC Corruption**	**Perceived Corruption Highly**
Informal Sector Activity	Petty Trading	27.0%	24.9%	24.7%
	Sub Farming	19.8%	24.5%	22.8%
	'Okada'	22.4%	20.5%	21.5%
	Cattle Rearing	4.9%	5.8%	4.9%
	Fishing	7.8%	6.1%	8.7%
	Tailoring	10.5%	11.3%	11.8%
	Mining	3.7%	3.6%	3.5%
	Quarrying	3.9%	3.3%	2.3%
Type of Treatment	Self	2.7%	1.9%	2.2%
	Traditional	2.5%	2.7%	2.5%
	Health Centre	48.8%	40.6%	55.7%
	Hospital	24.7%	31.7%	19.3%
	Drug Peddlers	8.1%	7.8%	8.7%
	Pharmacy	13.1%	15.2%	11.7%
	None	0.1%	0.2%	0%
Why Pay for FHC	Unaware Free	37.6%	37.6%	35.9%
	Asked to Pay	51.9%	51.9%	50.9%
	Paid Willingly	6.0%	6.0%	7.5%
	Others	4.5%	4.5%	5.7%
Location	Urban	47.5%	44.8%	44.6%
School	Rural	52.5%	55.2%	55.4%
	Went to School	67.5%	62.6%	69.8%
No of	Did Not	32.5%	27.4%	30.2%
Observations		**39366**	**17226**	**24920**

As shown in Table 4.8, about two thirds of the households we sample are engaged in petty trading, subsistence farming, or 'okada' economic activities. Over 70% of households prefer going to the health centre or hospital for treatment whenever sick. The same is true for households who answer Yes to FHC corruption and those who perceive corruption highly in the health sector. About 9 in 10 households answer that they are either unaware that the FHC service is free or are ask to pay by medical personnel.

About 55% of those living in urban areas answer No to FHC corruption compares to about 45% who answer yes. Similarly 55% of those living in urban areas perceive corruption highly in the health sector. In addition, about 6 out of every 10 heads of household that answer Yes to FHC corruption and those who perceive corruption to be high in the health sector went to school.

4.3.6 The Econometric Approach

Once the alternatives, attributes and attribute levels we include in the choice experiment are determine, it is possible to specify the model. The modelling framework that we use for this research project is the discrete choice analysis. This is selected because we gather data using a stated choice experiment, which ask respondents to choose between either participating in health insurance schemes A or B or not participating at all. In making those choices, each household is assumed to maximize their personal utility and select the alternative that provides the highest utility.

Discrete choice models are deeply rooted in utility theory. The primary basis of such a model is that it shows that the probability of a household choosing whether or not to participate in a health insurance scheme is a function of its attributes. Discrete choice models tend to combine choices made by households with the attributes of the available alternative and the attributes of the household.

Our dependent variables are perceived corruption, actual corruption (free health care corruption), and participation or non-participation in health insurance schemes A or B. The following questions form the basis of our dependent variables: (i) Each household is ask whether they pay for health services considered to be free within the three months prior to the survey. (ii) In addition, we ask households how they perceive corruption in the health sector. (iii) Finally, we ask whether they would like to participate in health insurance schemes A, B or not participate at all. The third question is our DCE question.

The type of model to use depends on the number of alternatives offered in the choice experiment. Ryan and Skatum (2004) suggest that the correct model to use to analyze the data depends on the cross elasticity of substitution across the possible response options given: yes or no to whether payment is made for children under five years old, pregnant women, and lactating mothers; four response answers to how households perceive corruption in the health sector – not corrupt, less corrupt, corrupt or very corrupt; and three response answers to participating in health insurance scheme A or B, or neither. When two alternatives are available, the binary logit/probit model is considered the most appropriate method to use. However, when three or more alternative choice options are available to the household, the Multinomial Logit (MNL), the Conditional Logit (CNL), and the Mixed Logit Model (MXL) are the most widely used discrete choice models in such scenarios.

We intend to carry out two main types of analysis in our study – to analyse the relationship between corruption (FHC corruption and households' perception of corruption in the health sector) and household characteristics, and the impact of corruption on participation in health insurance.

Consider a household choosing between *M* alternatives for participating in a health insurance scheme labelled A, or B, or not participating in either. The utility that household *i* will derive in choosing alternative *j* from *M* alternatives is given as

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{4.1}$$

However, if we assume utility to be linear in attributes, we have equation (4.2) below:

$$V_{ij} = \beta_j X_{ij} + \varepsilon_{ij} \tag{4.2}$$

Where $i = 1 \dots\dots\dots N$ households, $j = 0 \dots J$ alternatives, X is a vector of observed attributes relating to household *i*, and alternative *j*, and β is a vector of coefficients to be estimated. We can generate different choice models base on the assumption made about the distribution of the error terms. However, a rational household will choose the alternative that provides the highest level of utility.

The probability therefore that alternative *j* will be chosen from a set of *M* alternatives is

$$P(Y_i = j) = P(U_{ij} \geq U_{ik}), \forall k \neq j;$$

$$= P(\varepsilon_{ik} - \varepsilon_{ij} \leq \beta_j \mathcal{X}_{ij} - \beta_k \mathcal{X}_{ik}), \forall k \neq j \tag{4.3}$$

Estimable choice models are derived by assuming the distribution of the random component in equations (4.1) and (4.3), and the nature of the choice we model. Our FHC corruption outcome variable takes two values, that is, 0 and 1, hence allowing us to use the binary choice model. Therefore, assuming our error term is logistically distributed, we use a logit model in the estimation of the relationship between actual (free health care) corruption and household characteristics. On the issue of households' perception of corruption in the health sector, as each household has to choose one of the four options, we use MNL because it handles more than two choice options. The probability of household i participating in a health insurance scheme can be calculated if the maximum number of random variables is determined and an analytical solution does exist.

If however our error term in equation (4.2) is assumed to be an independent and identically distributed (IID) extreme value, then an analytical solution does exist. The probability therefore of household i participating in a health insurance scheme j is given by the following logit probability function:

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{j=k}^{J} e^{V_{ij}}} \tag{4.4}$$

The β parameters in V_{ij} here are fixed and hence do not vary over households. When applying an MNL to estimate equation (4.4), the following assumptions are made about the error terms: (i) they are independent – they are not correlated – and identically distributed (IID); (ii) they are Gumbel distributed; (iii) they are independent from irrelevant attributes (IIA), i.e. choice probabilities will all change in proportion to the introduction of a new alternative or the deletion of an existing one. Put in a simple way, the IIA property holds that adding or removing a third alternative does not affect the probability of choosing two alternatives in relative terms; and (iv) there is no taste heterogeneity, i.e. there are homogeneous preferences across respondents.

According to Ben-Akiva and Lerman (1985), the MNL has uniform cross elasticity, that is, the cross elasticity of the choice probability of any alternative, say I with respect to an attribute of alternative j, is the same for all alternatives, $i \neq j$. The wide use of the MNL model is attributed to its closed form solutions and its simplicity in use.

4.3.7 The Mixed Logit Model

Despite the popularity of the MNL in health economics literature, this model has many limitations. The MXL model extends the MNL and other logit models by allowing the coefficients to vary between respondents. It is this characteristic of the MXL model (the capacity to model preference heterogeneity) that gives it the potential to enhance the behavioural realism of the model, compared to the MNL and other logit models (Hensher and Green, 2003). In our case for instance, some households might have had a strong preference for say, participating in health insurance scheme A, and some for scheme B, and others for not participating in either.

However, in the other logit models, such variation in preferences can only be possible by interacting health insurance scheme attributes with socio-demographic characteristics of the households, with the likelihood that some of this preference heterogeneity is unrelated to observable household characteristics. As explained in the literature, to ignore this fact would result in reducing the behavioural realism of the model and even introducing bias into the estimates. Another limitation of the MNL model centres on the assumption that observations are independent, which is not the case with DCEs wherein respondents complete several hypothetical choice scenarios (ibid.).

Even though the MNL model is being widely used in the literature over the past three decades as the standard discrete choice model, researchers have highlighted its restrictiveness in terms of the Independence of Irrelevant Alternatives (IIA) assumption and hence the development of models that generalizes or relaxes the IIA property by modelling preference heterogeneity.[44] These limitations inherent in the MNL have given rise to the MXL, which has a number of attractions, and as explained by McFadden and Train (2000), provides a flexible, theoretical and computationally practical econometric method for any discrete choice model derived from the random utility method.

The central features of the MXL model are not limited to its ability to accommodate random taste variation across households and correlation across alternatives, hence generating flexible substitution patterns (Train, 2000). It also significantly improves model fit (Hensher and Greene, 2003); provides greater insight into choice behaviour (McFadden and Train, 2000); and provides better estimation of welfare. Other additional features include its ability to incorporate the fact that different customers have different preferences; and it is also sufficiently flexible for the coefficients of the attributes of the utility function to take any of the distributions such as normal, lognormal, triangular or uniform (Hensher and Greene, 2003). The MXL model provides abundant behavioural and physical interpretations. Studies have shown that the normal distribution is the most commonly used distribution of the random parameters.

From equation (2) above, we assume that ε_{ij} is IID extreme value type 1, allowing us to note that the information we need to make for an unobserved choice may induce two scenarios – correlation across the alternatives in each choice situation and correlation across the choice situations. A solution to this problem as Hensher and Greene (2003) suggest is to split the random

[44] The IIA concept implies that the relative probability of any two alternatives depends on the attributes of those two alternatives, that is, an additional alternative or changing the characteristics of a third alternative does not affect the relative probabilities between two alternatives.

term ε_{ij} into two additive parts – the first part looks at correlation over alternatives and heteroscedasticity and the other is IID across alternatives and households.[45] Following Hensher and Greene (2003), equation (4.5) below shows how the random component is split:[46]

$$U_{ij} = \beta_i X_{ij} + \varepsilon_{ij} \tag{4.5a}$$

$$U_{ij} = \beta_i X_{ij} + (\delta_{ij} + \varepsilon_{ij}) \tag{4.5b}$$

Here δ_{ij} is a random variable with mean 0 and its distribution across households and alternatives depends greatly on how the parameters and data relate to the household *i* and chosen alternative *j* and ε_{ij} is a random term with mean 0 that is IID over alternatives.

In the MXL model, the parameter β_i in equations (4.5a) and (4.5b) varies across households rather than being fixed as it is with the traditional logit models. This allows the coefficients of the explanatory variables (β) and the error term (ε) to be random, which accommodates random taste variation across households and correlation across alternatives, hence generating flexible substitution patterns. The MXL model requires integrating the probability of the MNL model, that is, P_{ij} in equation (4.4) over all possible values of β weighted by the density distribution selected – normal, lognormal, uniform or triangular. Given the density of δ by $f(\delta|\theta)$ where θ refers to the fixed parameters of the distribution and since δ is not given, our unconditional choice probability is given below:

$$P_{ij} = \int \frac{e^{(\beta_i' X_{ij} + \delta_{ij})}}{\sum_{j=1}^{J} e^{(\beta_i' X_{ij} + \delta_{ij})}} f(\delta|\theta) d\delta$$

$$P_{ij} = \int L_{ij}(\delta) f(\delta|\theta) d\delta \tag{4.6}$$

Here L_{ij} is the MNL probability that household *i* will participate in health insurance *j* for a given choice set; $f(\delta|\theta)$ is the probability density function and θ is a vector of "deep parameters" (McFadden and Train, 2000). Models of the form in equation (4.6) are known as MXL models because they are a mixture of logits with *f* as the mixing distribution.

The MXL has been used a lot in recent times and applied in health care using DCEs. However, most of the key topics studied include human resource policy issues such as policies that attract nurses, midwives, or doctors to rural areas, and differences in preferences for a rural job between

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45 For a thorough explanation of this aspect, see Hensher and Greene (2003).
46 This part of the work, uses Hensher and Greene (2003) to explain the econometrics of the MXL derivation

nursing students and practising nurses etc. (Rockers et al. 2013; Blaauw et al. 2010; Vujicic et al. 2010a; 2010b; Kruk et al. 2010; Rockers et al. 2012); WTP and health outcomes (Kjaer et al. 2013; Meenakshi et al. 2012; Veldwijk et al. 2013; Eberth et al. 2009); and economic evaluation, diagnostic and reproductive health (Lynn et al. 2013; Danyliv et al. 2012; Tinelli et al. 2012).

As equation (4.6) above has no close form solution, a simulation procedure has to be used to find the most appropriate θ – known in the literature as maximum simulated likelihood – and then compute the choice probability. Train (1998) explains that the maximum simulated likelihood estimator (MSLE) is a typical method use to estimate the probabilities. Estimation by maximum simulated likelihood (MSL) is undertaken in this study using 500 Halton draws.

The outputs of an MXL model include mean and standard deviation coefficients which measure the utility relative to each attribute conditional to the other attributes, and the random coefficients which estimate the degree of heterogeneity among respondents respectively.

4.3.8 Econometric Specification and Estimation Strategy

In this study, we used three types of models. We make use of the binary logit model to estimate how households' characteristics are associated with the likelihood of them paying for services that they should not pay for, i.e. *actual corruption*.

We apply a MNL model to estimate the relationship between the household's *perception of corruption* and household characteristics because there are three levels of perceived corruption (*less corrupt, corrupt and very corrupt)*.

Finally, to estimate the effect of corruption on the likelihood of participation in health insurance schemes, we make use of the MXL model which accommodates the violation of the IIA property of the errors and allows the explanatory variables to vary across households (Hensher and Greene, 2003).

The user written "mixlogit" command by A.R. Hole (2007) is used for the MXL model to estimate participation in health insurance. The statistical software STATA version 13.1 is used to estimate the model. Estimation results and summary statistics for the performance of each model were reported and are related to the overall model significance measured by chi-square (χ^2), quality of fit and variability of the model measured by pseudo R^2.

The linearized utility function that defines a household's participation in the health insurance scheme is given in equation (4.7) below:

$$U_{ij} = \beta_0 + \beta_{1i}Cost_j + \beta_{2i}Cov_j + \beta_{3i}Wait_j + \beta_{4i}Pub_j + \beta_{5i}Cont_j + \beta_{6i}Corr\_Pub_j + \eta_{ij} + \varepsilon_{ij} \quad (4.7)$$

Here β_0 is the intercept; $Cost$ is cost of the scheme, Cov is moderate coverage, $Wait$ is waiting time, Pub is public provider, and $Cont$ is non-public provider, which are the attributes of the health insurance scheme, and $Corr\_Pub_{ij}$ is the interaction effect of corruption on choice of public provider; and η is the error term that handles heteroscedasticity and correlation across alternatives and ε is the IID error term. We assume η to be normally distributed.

All the attributes are assumed to vary and be random, except cost, which is fixed. The application of the MXL model is based on intuition in deciding which attributes should vary and which should not. We assume the random coefficients to be normally distributed. As explained by Revelt and Train (1998), fixing the cost coefficient has many advantages but paramount among them is that it ensures the cost coefficient has the negative sign in our analysis. If we allow the cost coefficient to be random and normally distributed, it would imply that some households would be willing to pay more as the cost increases, which is counter-intuitive.

Households view their choice set as choosing between participating in three health insurance schemes – A, B or neither. Different sets of models are analysed in trying to solve a particular problem.

4.4 RESULTS

This section reports the results of our estimates of the effect of household characteristics on the likelihood of actual and perceived corruption, and of scheme characteristics on the likelihood of participation in given schemes. The sample includes 39,366 responses generated from 1,458 households who made nine choices each from three alternatives.

4.4.1 Regression Results

4.4.1.1 Relationship between Actual or Perceived FHC Corruption and Household Characteristics

Actual corruption is defined based on whether households pay for medical services for any of their members in the categories of children under five years old, pregnant women or a lactating mothers. We are interested in looking at the relationship between this type of objective corruption and household characteristics based on the scenario given above. As each household is faced with only two responses (Yes or No) per question, we used the logit model and have presented the coefficients and their standard errors (se) in Table 4.9.

Table 4.9: The Relationship between Corruption and Household Socio-Economic Characteristics

	FHC[1] Corruption Logit Estimates	Household's Perceived Corruption in the Health Sector[2] (Multinomial Logit Estimates)		
		Less Corrupt	Corrupt	Very Corrupt
Variables	Coefficients (Standard Errors)	Coefficients (Standard Errors)	Coefficients (Standard Errors)	Coefficients (Standard Errors)
Petty Trading[3]	0.28921 (0.07075)***	-0.0291 (0.09884)	0.60939 (0.11024)***	1.29079 (0.1228)***
Subsistence Farming	0.59757 (0.07335)***	-0.45953 (0.10969)***	0.84179 (0.11843)***	1.72880 (0.12929)***
'Okada'	0.36694 (0.07199)***	0.24801 (0.10367)**	0.94294 (0.11435)***	1.52526 (0.12671)***
Cattle Rearing	0.66548 (0.08674)***	-0.06254 (0.13758)	0.78614 (0.1467)***	1.46824 (0.15529)***
Fishing	-0.04902 (0.08124)	1.02246 (0.14092)***	2.13666 (0.14776)***	2.83177 (0.15779)***
Tailoring	0.48688 (0.07728)***	-0.3840 (0.11887)***	0.66356 (0.12617)***	1.7180 (0.13575)***
Mining	0.34541 (0.09349)***	0.34817 (0.16007)**	0.61966 (0.17201)***	1.70508 (0.17538)***
Log Household PCI	-0.41695 (0.03125)***	-0.91505 (0.05803)***	-1.02869 (0.05865)***	-1.26659 (0.05775)***
Distance H Centre	-0.02889 (0.00495)***	0.02659 (0.00842)***	-0.04889 (0.009)***	-0.14506 (0.00957)***
School[4]	-0.35640 (0.03087)***	0.77261 (0.05402)***	0.79795 (0.05418)***	1.26165 (0.05416)***
Urban[5]	0.00479 (0.02824)	-0.15983 (0.05079)***	-0.3616 (0.05142)***	0.21921 (0.04941)***
Age of Household Head	-0.00479 (0.00122)***	0.0013607 (0.00225)	-0.00025 (0.00226)	0.00871 (0.00221)***
Diseases	0.18261 (0.03079)***	0.42732 (0.05063)***	0.74279 (0.05168)***	0.673935 (0.05051)***
Remittance Received	1.62e-06 (1.09e-07)***	1.19635 (0.08288)***	1.23022 (0.0827)***	0.81721 (0.08294)***
News	0.52638 (0.03422)	0.58715 (0.05399)***	1.14843 (0.05723)***	0.71224 (0.05354)***
Constant	3.88735 (0.37462)***	9.80648 (0.69418)***	9.91224 (0.70061)***	11.79111 (0.69004)***
No of Observation	26244	26244		
Wald Chi2 (15)	-1127.26			
LR chi2 (45)		3962.72		
Prob >Chi2 (k-1)	0.0000	0.0000		
Log likelihood	-17372.241	-32385.98		

1. FHC stands for Free Health Care Corruption. 2. Not corrupt is used as the reference
3. The reference sector is quarrying. 4. No School is the base.
5. Rural is the reference location used.
*** p<0.01; ** p<0.05; * p<0.1.

All variables apart from the economic activity of fishing and urban location show a statistically significant relationship with FHC corruption. From the results we also see that the probability of a household paying for health services that are supposed to be free has a positive and significant relationship with the household receiving remittance, suffering from diseases (malaria or typhoid), living in an urban area, and the household head listening to news. All informal sector activities apart from fishing have a positive relationship with FHC corruption. On the other hand, a negative relationship exists between FHC corruption and distance to the health Centre, school, age of household head, and the informal economic activity of fishing.

Table 4.10 below presents the odds ratio and relative risks analysis of the relationship between corruption and households' characteristics. The odds for answering yes to FHC corruption is about 1.8, 1.9 and 1.6 times more likely for households whose primary economic activity is either subsistence farming, cattle rearing or tailoring respectively, than those whose economic activity is not among these. The implication is that FHC corruption is more likely for those in subsistence farming, cattle rearing or tailoring than those not involved in these three economic activities. The odds for answering Yes to FHC corruption for households who receive remittance and those who live in urban areas are equal to those households that do not receive remittances and those who live in rural areas respectively.

Table 4.10: **Relative Risks and Odds Ratios of the Relationship between Corruption and Household Characteristics**

	FHC[4] Corruption Logit Estimates	Households' Perceived Corruption in the Health Sector (Multinomial Logit) [5] Relative Risks		
		Less Corrupt	Corrupt	Very Corrupt
Variables	**Odds Ratio (Standard Errors)**	**Relative Risks (Standard Errors)**	**Relative Risks (Standard Errors)**	**Relative Risks (Standard Errors)**
Petty Trading[1]	1.3354 (0.0945)***	0.9713 (0.096)	1.8393 (0.2028)***	3.6357 (0.4464)***
Subsistence Farming	1.8177 (0.1333)***	0.6316 (0.0693)***	2.3205 (0.2748)***	5.6339 (0.7384)***
'Okada'	1.4433 (0.1040)***	1.2815 (0.1328)**	2.5675 (0.2936)***	4.5964 (0.5824)***
Cattle Rearing	1.9454 (0.1687)***	0.9394 (0.1293)	2.1949 (0.3220)***	4.3416 (0.6742)***
Fishing	0.95216 (0.0774)	2.780 (0.3918)***	8.4711 (1.2517)***	16.9755 (2.6785)***
Tailoring	1.627228 (0.1258)***	0.6811 (0.0810)***	1.9417 (0.2450)***	5.5734 (0.7566)***
Mining	1.4126 (0.1321)***	1.4165 (0.2267)**	1.8583 (0.3197)***	5.5017 (0.9649)***
Log Household PCI	0.6591 (0.0206)***	0.4005 (0.0232)***	0.3575 (0.0210)***	0.2818 (0.0163)***
Distance H Centre	0.9715 (0.0048)***	1.0270 (0.0087)***	0.9523 (0.0086)***	0.8650 (0.0083)***
School[2]	0.7002 (0.0216)***	2.1654 (0.1170)***	2.2210 (0.1203)***	3.5312 (0.1912)***
Urban[3]	1.0093 (0.0285)	0.8523 (0.0433)***	0.6966 (0.0358)***	1.2451 (0.0615)***
Age of Household Head	0.99521 (0.0012)***	1.0014 (0.0023)	0.9998 (0.0023)	1.0087 (0.0022)***
Diseases	1.2003 (0.0370)***	1.5331 (0.0776)***	2.1018 (0.1086)***	1.9619 (0.0991)***
Remittance Received	1.0000 (1.09e-07)***	3.3080 (0.2742)***	3.4220 (0.2830)***	2.2642 (0.1878)***
News	1.6928 (0.0579)***	1.7989 (0.0971)***	3.1532 (0.1805)***	2.0386 (0.1091)***
No of Observation	26244	26244		
Wald Chi2 (15)	1127.26			
LR chi2 (45)		3962.72		
Prob >Chi2 (k-1)	0.0000	0.0000		
Pseudo R2	0.0348	0.0577		
Log likelihood	-17372.241	-32385.98		

1. The reference sector is quarrying.
2. No School is the base.
3. Rural is the reference location used.
4. FHC refers to Free Health Care Corruption.
5. Not corrupt is used as the reference

*** p<0.01; ** p<0.05; * p<0.1.

4.4.1.2 The Relationship between Household Perceptions of Corruption and Household Characteristics

Households are also asked to choose on a scale of 1 to 4 (not corrupt to highly corrupt) how they perceive corruption in the health sector. Their responses are modelled along the lines of an MNL model to determine the relationship between households' perception about corruption in the health sector and socio-demographic factors. As each household had four options to choose from, the reference point used in the analysis is Not Corrupt. Coefficients and standard errors, and relative ratios for each variable are reported in tables 4.9 and 4.10 above for the three alternatives of perceived corruption looked at: Less Corrupt, Corrupt and Highly Corrupt.

From Table 4.9 above we can observe that a positive relationship exists between informal economic activities and households that perceive the health sector to be corrupt and less corrupt. Table 4.10 illustrates the magnitude of the relationship between household characteristics and their perceptions of corruption. The economic activities "okada", fishing and mining are 1.3, 2.8 and 1.4 times respectively more likely to characterize households that perceived the health sector to be fairly corrupt relative to those who perceived it as not corrupt. In addition, households that went to school and could listen to the news are about 2.2 and 1.8 times more likely to perceive the health sector to be less corrupt than those who perceived it as not corrupt. Equally, households that receive remittances are about 3.3 times more likely to see the health sector as fairly corrupt in relation to those who perceive it as not corrupt. Households that suffer from either malaria or typhoid are more likely to see the health sector as fairly corrupt than those who think the health sector is not corrupt.

On the other hand, households that received remittances and listened to the news are about 3.4 and 3.2 times more likely to perceive the health sector as corrupt relative to those who perceived it as not corrupt. Equally, those households that perceived the health sector as corrupt relative to those who considered it as not corrupt are more likely to be involved in all economic activities. For instance, those households that see the health sector as corrupt relative to not corrupt are about 8.5 times more likely to be involved in fishing. On another note, households that suffers from either malaria or typhoid are about 1.4 times less likely to perceive the health sector as corrupt relative to those who perceived it as not corrupt.

Moreover, households involved in any of the informal sector economic activities are more likely to perceive the health sector as highly corrupt relative to those who perceived it as not corrupt. The impact of their effect is almost twice as much as those who perceived the health sector to be corrupt. Households who went to school are about 3.5 times more likely to perceive the health sector as very corrupt than those who perceived it as not corrupt. All binary variables show that the households are more likely to perceive the health sector as very corrupt relative to those who perceived it as not corrupt.

4.4.1.3 The Impact of Corruption on Households' Participation in Health Insurance

We have data on the health insurance scheme attributes (coverage, cost, waiting time and choice of provider), corruption and participation. We therefore want to fit an MXL model explaining whether a household participates in health insurance schemes A or B or did not participate in either scheme based on the attributes of the scheme and corruption. The parameters from our model in equation (4.7) are therefore estimated using MXL specification.[47] The study makes use of 500 Halton draws for each sampled household to generate their simulated probability.[48]

The study looked at the impact of corruption on the households' participation in a health insurance scheme. A household in need of health insurance makes a decision to participate in any one of the schemes (A or B) or not to participate, based on the attributes of the scheme in question and the interaction terms between corruption and public provider. A critical issue when specifying an MXL is to choose the coefficients that are permitted to vary and what distribution they should take. Following from the literature, all variables apart from cost were specified as random. While random specifications of cost may improve model fit, however, a fixed cost coefficient may ensures that the estimate of cost utility has the right sign (negative) and is preferred for calculation and interpretation of WTP, as it avoids possible problems with dividing distributions on distributions (WHO, 2012). We allow all attributes of the scheme apart from cost to be random and had normally distributed coefficients because they could inform a household's participation or not in the health insurance scheme either positively or negatively. We however specify the cost coefficient to be fixed which had several advantages. This ensures that the cost coefficient has the right sign: a normally distributed cost coefficient implies that some households may prefer a health insurance scheme with higher cost, which is counter-intuitive. In addition, as Ruud (1996) explains, fixing at least one coefficient in the model helps empirical identification, especially in applications using cross-sectional data.

To understand how corruption impacts households' participation or not in a health insurance

[47] This study used the user-written program "mixlogit" by Hole (2007) in stata.
[48] This work used 500 Halton draws because it is the most widely used number of draws and, as Train (1999) explains, a large number of draws are needed in most cases to assure reasonably low simulation error in the estimated parameters.

scheme, we allow our measure of corruption to interact with one of the DCE attributes – public provider. We chose this attribute because in previous work (Chapter 3 of this thesis) we found out that households were willing to pay less for public providers. The Reasons advanced for this relates to the level of corruption in public provider schemes.

Table 4.11 below presents the estimation results of our MXL model for our main sample. The mean coefficients of our estimates are presented alongside their standard deviations.

Table 4.11: The Impact of Corruption on Households' Participation in Health Insurance – Mixed Logit Model Result

	Participation in Health Insurance (Main Model with FHC Corruption)		**Participation in Health Insurance (Main Model with Perceived Corruption)**	
Variables	**Mean (SE[1])**	**SD[2] (SE)**	**Mean (SE)**	**SD (SE)**
Cost	-0.00003 (5.18e-06)***		-0.00003 (5.18e-06)***	
Coverage	0.36598 (0.01913)***	0.39426 (0.02711)***	0.36714 (0.01914)***	0.39376 (0.02711)***
Waiting Time	-0.00677 (0.0011)***	0.03169 (0.001)***	-0.0068 (0.0011)***	0.0316 (0.00098)***
Public Provider	0.07325 (0.03873)*	0.08236 (0.13421)	0.11276 (0.06451)*	0.07196 (0.13214)
Non Public Provider	0.6919 (0.03505)***	0.55507 (0.04972)***	0.69372 (0.03517)***	0.565288 (0.0503)***
FHCCorr_Public	-0.02934 (0.00718)***	0.43805 (0.088)***		
CorrPerc_Public			-0.02054 (0.02681)	0.01685 (0.05799)
HI Scheme 1	3.32962 (0.09704)***		3.32085 (0.09699)***	
No of Observation	39366		39366	
LR Chi2 (k-1)	2373.56		2375.98	
Prob >Chi2 (k-1)	0.0000		0.0000	
Log likelihood	-9762.8307		-9761.4837	

1. SE stands for Standard Error.
2. SD stands for Standard Deviation. The sign of the estimated standard deviations is irrelevant: they are to be interpreted as being positive (See Hole, 2013 for an explanation of this statement).
*** Significant at 99% confidence level; ** Significant at 95%; and * Significant at 90%.

Using Table 4.11, we can compare the impact of the interaction terms "FHCCorr_Public" and "CorrPerc_Public" on participation in a health insurance scheme. Generally, all our variables apart from the interaction term "CorrPerc_Public" are statistically significant. All coefficients in the overall model apart from public choice of provider reveal the existence of substantial preference heterogeneity, that is, all coefficients except public choice of provider are found to have statistically significant standard deviations for both types of corruption models. Comparing both samples – model with FHC corruption and corruption perception, the results are almost the same.

The above results show that the attribute cost has a negative sign and is statistically significant, implying that the probability of participating in a health insurance scheme goes down as cost rises. Coverage and non-public provider are the main attributes that significantly determine whether the household will participate in the health insurance scheme, and they have positive signs, implying that households will increase their participation in health insurance if there is an improvement in coverage and non-public provider. This confirms that the households' choice of participation in the health insurance scheme is consistent with consumer theory.

Our results also indicate that, on average, the likelihood of households participating in the health insurance scheme is higher when the cost of the scheme and waiting time are low. However, households prefer comprehensive coverage and choice of provider to the other attributes. A further look at the magnitude of the coefficients and standard deviations relative to the mean, tells us that for our overall sample with FHC corruption, about 82.3% of the households prefer moderate to simple coverage and 41.5% prefer shorter to longer waiting times.[49] However, 47.3% prefer to participate in a public provider scheme without any FHC corruption. For our sample with perceive corruption, 17.6% preferred simple to moderate coverage while 41% prefer longer to shorter waiting times. About 11% of households prefer to participate in a scheme without perceive corruption.

We further look at the impact of both types of corruption on participation in health insurance, based on the type of location of the household, that is, rural versus urban. Table 4.12 below shows the MXL results.

[49] The percentages are given by 100* Φ (-b/s) where Φ is the cumulative standard normal distribution, b is the mean and s is the standard deviation of the coefficient. For a better understanding of this, see Hole (2007).

Table 4.12: The Impact of Corruption on Participation in Health Insurance: Mixed Logit Model Results based on Location

	RURAL HOUSEHOLDS		URBAN HOUSEHOLDS	
	Participation in Health Insurance (With FHC Corruption)	**Participation in Health Insurance (With Corruption Perception)**	**Participation in Health Insurance (With FHC Corruption)**	**Participation in Health Insurance (With Corruption Perception)**
Variables	**Mean (SE[1])**	**Mean (SE)**	**Mean (SE)**	**Mean (SE)**
Cost	-0.00004 (7.13e06)***	-0.00004 (7.13e-06)***	-0.00002 (7.65e-06)***	-0.00003 (7.59e-06)***
Coverage	0.36776 (0.02642)***	0.36644 (0.0264)***	0.41971 (0.02889)***	0.41214 (0.02828)***
Waiting Time	-0.0077 (0.00152)***	-0.00799 (0.0264)***	-0.00557 (0.00158)***	-0.00591 (0.00158)***
Public Provider	-0.01042 (0.05670)	-0.06138 (0.0847)	0.14071 (0.05623)**	0.18348 (0.08268)**
Non Public Provider	0.57496 (0.04534)***	0.57442 (0.04532)***	0.85013 (0.05466)***	0.84711 (0.05453)***
FHCCorr_Public	**-0.06954 (0.07486)**		**0.04814 (0.08683)**	
CorrPerc_Public		**0.01016 (0.03771)**		**-0.00243 (0.03798)**
HI Scheme 1	3.56783 (0.13473)***	3.57245 (0.13481)***	3.12295 (0.1435)***	3.16984 (0.14306)***
Variables	**SD[2] (SE)**	**SD (SE)**	**SD (SE)**	**SD (SE)**
Coverage	0.40211 (0.0379)***	0.40124 (0.03803)***	0.41333 (0.04101)***	0.39594 (0.04124)***
Waiting Time	0.03223 (0.00133)***	0.03217 (0.00132)***	0.023023 (0.00139)***	0.0305 (0.00139)***
Public Provider	0.32714 (0.09883)***	0.20036 (0.20867)	-0.00416 (0.00495)	-0.13309 (0.16702)
Non Public Provider	0.36282 (0.09106)***	0.36342 (0.0905)***	0.69893 (0.06938)***	0.69775 (0.06741)***
FHCCorr_Public	**-0.04071 (0.39902)**		**0.58246 (0.1128)*** **	
CorrPerc_Public		**-0.12752 (0.06068)** **		**0.00564 (0.08107)**
No of Observation	20655	20655	18711	18711
LR Chi2 (k-1)	1330.31	1332.20	11109.59	1127.7
Prob >Chi2 (k-1)	0.0000	0.0000	0.0000	0.0000
Log likelihood	-5105.3814	-5104.8387	-4561.0962	-4553.0769

1. SE stands for Standard Error
2. SD stands for Standard Deviation;
*** Significant at 99% confidence level; ** Significant at 95%; and * Significant at 90%.

From the results in table 4.12, we see that for both types of corruption, the probability of a household participating in health insurance increased with coverage and non-public provider but goes down with cost of the scheme and waiting time, irrespective of whether the household is in rural or urban area. However, public provider decrease the probability of participation for rural households but increases it for urban households. For rural households, the interaction term, FHCCorr_Public decrease the probability of participation in a public provider health insurance while CorrPerc_Public increases the probability of participation in such schemes, though not statistically significant. On the other hand, we see an opposite picture for urban households, that is, the interaction term FHCCorr_Public increase the probability of participation while CorrPerc_Public decreases the probability of participation in public provider schemes. The implication here is that irrespective of the fact that corruption is not significant, households will participate in a health insurance scheme.

Understanding households' preference heterogeneity, the results reveal that in rural households, all variables apart from FHCCorr_Public and public provider (for perceived corruption) show the existence of substantial preference heterogeneity. For urban households on the other hand, all variables apart from public provider and CorrPerc_Public show that the sample exhibits taste variation. The implication is that there is considerable variation across households regarding the effect of coverage, waiting time and non-public provider, or those households' whose preferences for these variables vary from household to household. On the impact of corruption on participation in a public provider health insurance scheme, there is considerable variation across households regarding the effect of FHCCorr_Public and CorrPerc_Public in urban and rural areas respectively.

A further inspection of our result reveals that in rural households using both measures of corruption, 82% of households prefer moderate to simple coverage, about 60% of households prefer longer to shorter waiting times, and about 95% prefer a non-public provider to a public provider health insurance scheme. Furthermore, our results reveal that 57% of rural households prefer to participate in public provider schemes without corruption, irrespective of the type of corruption. For urban households, 53% of households prefer to participate in a health insurance scheme without FHC corruption, whereas about 67% prefer a health insurance scheme wherein households do not perceive corruption in the health sector.

4.4.1.4 Willingness to Pay to Participate in Health Insurance

The impact of corruption on a households' participation in health insurance is also looked at in terms of households' WTP to participate in a health insurance with and without corruption.

Table 4.13 below shows the WTP to participate in a scheme with corruption.

Table 4.13: WTP[1] to Participate in Health Insurance with and without Corruption

Variables	Main Sample	
	SLL	USD ($)
FHCCorr_Public	(978.00)	0.22
CorrPerc_Public	(684.67)	0.16

The values in brackets are negative, which implies a WTP to participate in a publicly provided health insurance scheme for a reduction in corruption
1 The WTP figures are in the local currency – Sierra Leonean Leones (SLL).
2. The values in brackets are negative, which implies a WTP to participate in a publicly provided health insurance scheme for a reduction in corruption.

From Table 4.13, we see that WTP is higher for publicly provided health insurance schemes with FHC corruption. WTP to participate in health insurance for a reduction in corruption is about 43% higher for health insurance schemes with FHC corruption than with corruption perception. In general, households are willing to pay more to participate in a health insurance scheme for a reduction in FHC corruption. This agrees with the literature on corruption, as respondents are WTP more to control actual corruption (Chetwynd et al. 2003; Rose-Ackerman 1997; Kenny 2006).

4.5 DISCUSSION AND CONCLUSION

This chapter has studied the impact of corruption on households' participation in health insurance using MXL models. It has also looked at the relationship between the types of corruption and household characteristics using Logit and MNL models.

Our study reveals that the relationship between households' perceptions of corruption and households' characteristics has contrasting relationships. For instance, a negative relationship exists between the informal sectors and those households' that perceive there is less corruption in the health sector, while a positive relationship exists with those households' that perceive the health sector to be very corrupt. In addition, a positive relationship exists between households that perceive the health sector to be less corrupt and the following variables: distance to health centre, urban location and remittance received. On the contrary, a negative relationship exists between these variables and households' that perceive the health sector to be highly corrupted. Generally, there are differences between FHC corruption (actual corruption) and households' perception of corruption in the health sector.

Irrespective of the sample we look at, participation in a health insurance scheme increased with coverage and type of non-public provider, but decreases with cost and waiting time. For the main sample, participation in health insurance decreased also with corruption. On the impact of corruption on participation in health insurance using our location, we see that corruption does not significantly affect households' decision to participate or not in health insurance. Intuitively, all they care about is their health and not corruption because they know corruption is prevalent.

Our study also reveals that households strongly prefer to participate in health insurance schemes rather than not participating at all. This is evidence by the large positive coefficients for the health insurance schemes (health insurance scheme 1 in tables 4.11 & 4.12). This supports other studies on the issue of participation in health insurance, which show that informal sector households will pay more to participate in such schemes.

Our findings also show that corruption generates substantial additional cost to households. To ascertain the extent to which corruption would impact health insurance in terms of overall societal effect is difficult. However, we use WTP to participate to help look at this impact. WTP to participate estimates can provide some indication of the value of the cost households place on corruption. It is evident in our WTP to participate estimates that WTP to participate in health insurance is about 43% higher for FHC corruption with a public provider. WTP to participate is higher in schemes with corruption because of the high cost of corruption. When there is corruption in such schemes, it costs households extra because providers transfer the cost to members. One of the points we need to take into consideration is the fact that health care is a necessity good. In the case of India, as Kenny (2006) explains, even the very poor were willing to pay more to see an improved quality of services.

We show how the MXL model can be used to gain better understanding into households' decision to participate or not in health insurance schemes. Taking both types of corruption into consideration, we see that the impact of FHC corruption on participating in health insurance is greater than households' perception of corruption in the health sector. This is the case in the literature, as actual corruption (FHC corruption) tends to have a more direct and stronger impact than perceptions about corruption. As Olken (2009) explains:

> Measuring perceptions about corruption rather than actual corruption skirts the inherent difficulties involved in measuring corruption directly, but raises the question of how those being surveyed form their perceptions in the first place, and how accurate these reported perceptions actually are. (pp. 950)

One of the key findings of our study is that the impact of FHC corruption is higher in urban areas than rural areas.

Our study suggests that corruption impacts greatly on participation in health insurance. Therefore, the government and health insurance authorities need to take initiatives to curb corruption or else essential medicines and medical equipment meant for the poor and less fortunate will not reach them. As at 2013, Sierra Leone spends 11.8% of her GDP on health; has a per capita health expenditure of $96, and an OOP health expenditure of 61.3% of total health expenditure (World Bank, 2013). However, low-income countries and Sub-Saharan Africa respectively spend 5.5% and 5.7% of their GDP; have a per capita health expenditure of $277 and $101, and an OOP health expenditure of 45.3% and 34.6% (ibid.). One of the key arguments for the appalling performance of the health care sector in Sierra Leone is attributed to corruption.

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Chapter 5 – Ability to Pay for Health Insurance: A Case Study of Informal Sector Workers in Sierra Leone

5.1 INTRODUCTION

The rich can afford quality healthcare whereas the poor find it difficult to access. In addition, the bulk of the population live in rural areas or in urban slums and find it difficult to access health care because of the high cost and unnecessary bureaucracy.

Willingness to Pay (WTP) is one of the most widely discussed and written topics in health economics. The majority of studies look at households or individuals' WTP for a health outcome, including health insurance. WTP has many definitions including that given by Kielhorn and Schulenburg (2000), which is the maximum amount of money an individual or household is willing to pay to obtain a particular benefit such as a health care service. It is the monetary value which households place on each health insurance attribute. WTP is a stated preference approach that involves asking people directly what they would be willing to pay for goods and services in the future. WTP aims to determine how much individuals are prepared to pay to reduce their risk of mortality and morbidity (Mooney, 2003). WTP is considered as the demand curve for health care or insurance represented by the negative relationship between cost and quantity of care or insurance sought.

WTP expresses how much a household is willing to pay for a commodity or an improvement in a service. What it fails to explain is whether this amount proposed by households is really within their reach. Schmidt et al. (2006) concluded that WTP is a very loose 'proxy indicator for ability to pay'. Almost all studies in developing countries have looked at people's or households' WTP by studying their needs and preferences, hence failing to bring out their Ability to Pay (ATP); that is, whether these households have the resources to actually pay for the care or insurance. When needs and preferences (WTP) are backed up by affordability (ATP) for the goods or services in question, then the demand for them is said to be effective.

ATP is largely determined by whether health insurance is affordable using own wealth or if households have access to the requisite capital when choosing health insurance. Bundorf and Pauly (2006) argued that the affordability of health insurance is an ambiguous term and that there is neither an accepted nor a rigorously discussed definition of affordability in economics; but the term is used widely in housing. They concluded that affordability is based not only on what people could buy, rather on what they actually bought. Not much work on ATP for health care has been done in Sub-Saharan Africa. A few papers have looked at child survival in the Central

African Republic (Weaver et al*.,* 1996); the impact of user charges in the Ashanti-Akim District of Ghana (Waddington and Enyimayew, 1990); and Swaziland (Yoder, 1989). To the best of the knowledge of the authors, nothing has been done on the ATP for health insurance in developing countries.

Health care cost is a burden on poor households in poor and developing countries. In Sierra Leone, out-of-pocket (OOP) health care expenditure is high and serves as a hindrance to hospital visits (World Bank, 2010) and so analysing affordability will guide policymakers in Sierra Leone's health care system, as this issue is crucial to getting an affordable health insurance programme for the informal sector. Access to health care is a serious issue in Sierra Leone, more so among poor households in the informal sector. Health care is expensive in Sierra Leone, and higher OOP health expenditures limit visits to the hospital. Having health insurance improves health care by improving access to health services and has a positive impact on health status (Escobar et al*.,* 2010). A strong health care system balances prevention and intervention strategies, provides health care education for citizens, maintains an active workforce of health care providers, and allocates sufficient resources to confront illness (*ibid.*). The purpose of health insurance is three-fold: 'increase access and use by making health services affordable, improve health status through increased access and use, and mitigate the financial consequences of ill health by distributing the costs of health care across all members of a risk pool' (*ibid.*).

This study goes beyond WTP by exploring respondents' ATP, hence analysing their effective demand for health insurance. It also addresses the question of who among the informal sector households can afford to pay for health insurance. Policymakers often see the problem as one of affordability and seek a practical solution to this problem. It contributes to the literature by being the first study to look at ATP for health insurance for Sub-Saharan Africa (SSA) in general, and in Sierra Leone in particular, after controlling for endogeneity using different methods. It is also the first study in SSA to make use of the discrete choice experiment method in analysing ATP for health insurance.

The remaining sections of this chapter are structured as follows. First a literature review of ATP is presented, followed by the data source and description. Next, it estimates the econometric model and present the results thereof. The final section is a discussion of the results and conclusion.

5.2 THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Though used frequently in housing, the definition of affordability in economics is still not exhaustively discussed.[50] Hancock (1993) argued that the definitions of affordability must distinguish between the individual or household conception of what is and is not affordable, and society's judgment. However, Bundorf and Pauly (2006) gave two definitions of affordability; normative and behavioural. Normatively, they defined affordability as what people could buy whereas behaviourally, it is what people actually buy. ATP takes into account a household's income and their expenditure on health. Effective demand is defined as the proportion of WTP to household's health expenditure. Bhat and Jain (2006) use the extent of a household's health insurance purchase as the total amount of premium paid per year divided by the total expenditure per year of the household as their ATP threshold.

ATP as defined by Weaver et al. (1996) is the proportion of health care expenditure per episode of illness compared to monthly household consumption. They measured ATP as the proportion of monthly expenditure for health care to monthly household consumption. Bundorf and Pauly (2006) observed that people could pay for health insurance if they are able to sacrifice other things to make it affordable, but affordability depends on more than the price of the product. They concluded that affordability depends on the price of other products and external situations of the buyer such as family size and cost of living.

Measuring affordability is crucial and there are four main measures of affordability used in the literature:

(1) The **affordability index** approach compares per capita health spending (health expenditure) and median income (including WTP and household income). This approach as used by Ghosh and Mondal (2011), Bhat and Jain (2006) and Weaver et al. (1996) measured ATP as monthly expenditure for health care as a percentage of monthly household consumption.

(2) The **poverty measure** approach uses the poverty threshold, which is the minimum level of household income as a proportion of the national poverty line. Bundorf and Pauly (2006) used this method in their study.

(3) The **normative approach** to affordability looks at affordability in terms of what people will buy. Also used by Bundorf and Pauly (2006) and Weaver et al. (1996), it measures ATP as the monthly expenditures for health care as a percentage of monthly household consumption.

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[50] Affordability and Ability to Pay (ATP) are used interchangeably in this work

(4) The last measure is the **behavioural approach** to affordability, which, measures people's ability to buy the goods in question and was used also by Bundorf and Pauly (2006).

This case study uses the fourth definition of affordability, which uses an affordability threshold as an explanatory variable in a regression equation from which we can estimate the ability to pay. Other methods simply determine an affordability threshold and from the data, state the number of households that have the means to pay for the stated product.

Many studies have used the normative approach to affordability. The main criticism of this approach is the level of subjectivity in its use; that is, determining what is too much and too little relative to expenditure. What will be too much for one household within a sector will be considered too little by another household within the same sector. Very few studies have looked at health insurance affordability by proposing a theoretical model and thus estimating who can and cannot afford health insurance. Bundorf and Pauly (2006) used this method to estimate affordability. Inasmuch as their work is widely used in the literature, it is still not without its own shortcomings. Bradley (2009) explained that their work suffered from endogeneity bias, omitted variables, and had identification problems. In trying to solve these problems, Bradley accounted for unobserved heterogeneity in consumer characteristics; health plan quality and health plan prices that lead to endogenous regressors of an insurance choice model. Health insurance choice was modelled along the lines of a discrete choice where unobserved heterogeneity can bring about market failure. This study was also modelled along those lines.

Asgary et al. (2004) concluded that lower income groups lack the ATP and as such are more sensitive to price changes in health care services. They argued that the lack of access to health insurance has a negative impact on the health of households and individuals. It is evident that health insurance plays a key role in reducing the influence of high costs of health care (high OOP) on households' economic well-being by turning unpredictable health expenditure into predictable insurance payments.

Weaver et al. (1996), in their study in the Central African Republic (CAR), used the proportion of monthly health care expenditure per episode of illness as a percentage of monthly household consumption as their ATP threshold. A national survey of CAR's population was conducted to determine their willingness and ATP for quality improvement in facility maintenance, supervision of personnel, and drugs to treat diarrheal diseases, acute respiratory infections, malaria, intestinal parasites and sexually transmitted diseases. Their results show that amongst those who sought modern care, their mean total expenditure was 2.6% of monthly household consumption and that total expenditure ranged from 1.9% for those who purchased medicines without visiting a facility, to 4.8% for those who visited a private facility. Their main finding was that, if current household health expenditure as a percentage of household consumption was used as the ATP threshold, the population would be able to pay the estimated cost of all seven quality improvements proposed for the user fee programme.

In their study of the impact of user charges in the Volta region of Ghana, Waddington and Enyimayew (1990) found that people did not have the ability to pay for drugs being prescribed. Inability to pay was clearly an issue for some people and there was a trade-off between setting new levels of charging realistic fees, and the ability of the average Ghanaian to pay those fees. For them, the ATP threshold is the current user fee.

Ghosh and Mondal (2011) explored whether the urban poor really lacked the capacity to pay for health insurance in Mumbai, India. They defined their affordability threshold as 'above poverty' status. They found that 40% of the population studied were unable to pay and had no purchasing power for such schemes. The two most relevant reasons that the subjects advanced were the informal nature of their occupation and the absence of a fixed monthly income.

5.3 DATA SOURCE AND DESCRIPTION

5.3.1 Study Area and Sampling

The data used in this study comes from a discrete choice experiment (DCE) survey we conduct between April and August 2013. A total of 1670 households in the northern and western regions of Sierra Leone are interviewed, and 1458 households' data are used for the final analysis. A two stage stratified sampling method was used to identify the households. Eight informal sectors are considered for the study: petty trading, subsistence farming, commercial bike riding (Okada riders), cattle rearing, tailoring, fishing, mining, and quarrying. These sectors are chosen because they represent the most predominant informal sector activities in Sierra Leone.

A face-to-face method is used to administer the questionnaire to the households we select. The questionnaire is divided into three sections. The first looks at the identification of the informal sector the household is engaged in. The second presents the discrete choice experiments, and the final section looks at the socio-demographic characteristics of the households.[51] The questionnaire starts with a detailed explanation of the attributes and the levels for respondents to understand the various choice combinations. Since the majority of the sample comprised of households who are not well educated, it is important to thoroughly explain the entire process to ensure full understanding. The household is the economic unit used in this study and is chosen

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[51] Chapter 3 of this thesis gives a detailed description of the discrete choice experiment carried out.

randomly from both strata. The choice of the household as the economic unit in this study stems from the notion that in poor informal households, the economic decision to purchase health care among these rural and mostly farmer households is more likely to be a household decision rather than an individual one.

The data we collect is entered into Microsoft Excel by a team of data entry staff and checked for consistency.

5.3.2 The Discrete Choice Experiment

This study uses the Discrete Choice Experiment (DCE) to address the issue of ability to pay for health insurance.[52] DCE is an attribute-base measure of benefit technique that is use in health economics to address a wide range of policy issues (Ryan *et al.,* 2010; de Bekker-Grob *et al.,* 2012). In the DCE, we present households with a combination of hypothetical scenarios combining attributes and levels we identify as important to the health insurance scheme. The DCE involves separating the health insurance scheme into distinct attributes and modelling the satisfaction as a behavioural response, which comprises a random and a systematic component. The attributes households choose are constant in each scenario, but the levels that describe each attribute vary systematically across scenarios; hence respondents choose the preferred option for each question (de Bekker-Grob *et al.,* 2012). In conducting this DCE, the researchers take into consideration the following requirements: that the health insurance scheme is made up of bundles of attributes; that the most important attribute(s) of the health insurance scheme is/are identified; that the attributes and levels chosen are actionable; and that the households are familiar with the concept and overall objective of the study and can rate the health insurance scheme (Ryan *et al.,* 2010).

Four attributes of health insurance are explored, each with three levels. The attributes and levels must be mutually exclusive, quantifiable and comprehensive. The attributes use is determine through literature reviews and discussion with expert reviewers. The attributes chosen and their levels include cost (4,000SLL, 6,000SLL, and 10,000SLL),[53] coverage (simple, moderate and comprehensive), waiting time (45 minutes, 60 minutes and 90 minutes), and type of provider (private, public and contracted or non-public). [54]

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[52] For an in-depth explanation of DCE, see Chapter 2 of this thesis.
[53] SLL refers to Sierra Leonean Leones (Local currency used in Sierra Leone)
[54] See chapter three for a definition of each of the attribute levels

The 4 attributes, each with their 3 levels represents 81 possible health insurance choice scenarios.[55] As this number is quite cumbersome, the number of choice sets is limited to 18 and comprises two blocks, hence allowing 9 choice sets per household. That number of choice sets is quite within the acceptable range for DCE studies (de Bekker-Grob *et al.,* 2012).[56] A tenth fixed-choice question is used to evaluate internal consistency and reliability. The statistical software SPSS and experimental design website by Burgess (2007) are used to generate and check the efficiency of the design.

There are two alternatives or options each household is to choose from: Health Insurance Scheme A or B. Rather than forcing households to choose between the two alternatives, they are first ask to indicate which scheme they prefer, and then whether they will participate in their chosen scheme. Table 5.1 gives an example of this type of DCE question design format. This approach, which uses a two-stage design, employs two discrete choice questions. Within the health economics literature this method is used by Vujicic *et al.* (2010) in comparing forced and non-forced choices when looking at nurses' preferences for job locations in Liberia; Marshall *et al.* (2009) to investigate preferences and up-take rates for colorectal cancer screening; and more recently Sivey *et al.* (2012) to investigate why junior doctors do not want to become general practitioners.[57] Following Vujicic *et al.* (2010), a two-stage method is used mainly to enable the researchers to estimate separately the household's probability of participation in the hypothetical health insurance scheme and need for health insurance. This help to determine whether attribute levels are in an appropriate range. If those who chose not to participate in the scheme are more than those who chose to participate, it would suggest that the attribute levels are set too low.

An example of a choice question is shown in Table 5.1 below.

[55] The 81 choice scenarios comes about by ($3^4 = 81$) which is (# of Levels $^{\text{\# of Attributes}}$)

[56] See chapter 2 of this thesis for acceptable choice sets to use and why.

[57] MABEL is 'Medicine in Australia: Balancing Employment and Life' and much of their work can be found at http://www.mabel.org.au

Table 5.1: An example of a DCE question format as used in the study[58]

Attributes	**Health Insurance Scheme A**	**Health Insurance Scheme B**
Coverage **Waiting Time (Minutes)** **Type of Provider** **Cost (SLL)**	Comprehensive 45 Public 4000	Simple 90 Contracted 6000
Which scheme do you prefer?		
Are you willing to participate in your chosen scheme? Yes or No		

5.3.3 Data Set

The data for this study is derived from a DCE methodology and a survey of household socio-economic characteristics. The main variables are under the various divisions of perceived need, participation in health insurance and ATP for health insurance, and are explained thus:

Need for Health Insurance: Four definitions of need for health care services are proposed by Culyer and Wagstaff (1993): need can be defined with respect to the individual's health status; it is the capacity to benefit from health care; it is the level of health care expenditure; and it is the minimum amount of resources required to exhaust capacity to benefit.

The definition of need used in this study is "need defined in terms of the households' health status"[59]. We create a binary subjective health indicator by dividing the 4-level household health into good and poor health. The question we ask in the survey to collect the household's subjective health status, which, defines the variable need is "which category best describes your household's health status?" (1) Good, (2) Fairly Good, (3) Not so Good, and (4) Poor. The binary variable takes 1 if the household's health status is 3 or 4 and 0 if it is 1 or 2.

Perceived need for health insurance is determine by households' socio-economic factors such as the age of the head of the household, the head of household's level of education, the type of economic activity the household was engaged in, the distance to the nearest health centre (which determines cost of access to treatment), and location of the household, that is whether the household is located in a rural or urban area.

Participation in Health Insurance: This is defined in our model as the variable "PATRT" and is captured in the DCE when households are presented with hypothetical health insurance schemes and asked whether they will participate in their chosen scheme. Participating in the health

[58] We replace henceforth contracted provider with non-public provider throughout this paper to give clearer understanding

[59] NEED and Ill health are used interchangeably in this work.

insurance scheme is determined by the attributes of the hypothetical health insurance scheme – cost, waiting time, coverage and type of provider – whether the household needs health insurance, and the households' financial capacity to pay for that insurance.

Ability to Pay for Health Insurance: Ability to Pay (ATP) takes into account households' income and their expenditure on health. In determining ability to pay, two key variables are of interest, namely the need for health insurance and financial capacity to pay for it.

Household's Financial Capacity to Pay (FCP): This is the difference between a household's effective income and their subsistence expenditure requirements, or put in another way it is effective income net of subsistence expenditure.

$$FCP_i = CExp_i - Sexp_i;$$

where FCP is financial capacity to pay for health insurance; Cexp is consumption expenditure of the household; and Sexp is subsistence expenditure of the household. The process of how the subsistence expenditure of the household is estimated is explained in Equation 5.13 below.

Effective Income: Estimating permanent income over the life cycle of a household is almost impossible, as is information on households' future income, assets, or propensity to borrow or lend. To solve these fluctuations often experienced in income data, this study used the household's consumption expenditure as a proxy for effective income. This is based on the following reasoning:

- Income data is affected by random shocks whereas consumption data conforms better to effective income. In defining capacity to pay, Xu *et al.* (2005) explained that it is important to minimize or remove the effect of random shocks on income.
- It is a general practice in economics that in household surveys, expenditure data is considered more reliable than income data. This lends credence to the point that in developing countries, the respondents to surveys in large informal sectors normally do not reveal their true income for various reasons (Deaton, 1992). Income data is considered an unreliable measure because it can be under-reported, it can be seasonally dependent, and it does not necessary capture longer-term income in low-income settings (Makinen *et al.,* 2000).

Subsistence Expenditure: Households need to first meet their basic subsistence needs or they will not be in a position to buy health services, hence a household's capacity to pay for health services should not be determined by its total effective income. Having a clear and standard definition for subsistence expenditure (Sexp) comes with its own challenges. Food expenditure will not capture the actual subsistence expenditure of the household, international comparability of the poverty line is difficult, a household's capacity to pay by using actual food expenditure can lead to underestimates, and there are problems constructing food purchasing power parity (PPP) conversion factors.

To solve these problems, the subsistence expenditure of the household is defined as the product of the food poverty line and equivalent household size. Xu (2005) defines the subsistence expenditure of the household as the basic requirement a household needs to maintain a starting point in life. Xu (2005) estimated the subsistence expenditure of the household as

$$Sexp_i = fpl * eqsize_i$$ [60]

An affordability (ability to pay) threshold is defined based on the households' FCP, which is, the consumption expenditure less the subsistence expenditure of the household. ATP is defined based on the sign of the variable λ in the recursive bivariate probit equation discussed in a later section. A positive and significant λ will indicate a household that perceives a need has the ability to pay for health insurance, while a negative λ will imply that a household that perceives a need does not have the ability to pay for it. Wang and Rosenman (2007) used a similar notation when looking at health insurance in rural China. The coefficient η measures the extent to which perceived need affects the probability of participating in the health insurance scheme while α measures the impact of the affordability threshold on participation in health insurance (see equations 5.1 – 5.12). The variables used and their definitions are provided in Table 5.2:

[60] The food poverty line (FPL) for Sierra Leone is taken from Statistics Sierra Leone (SSL)

Table 5.2: Variable Definitions

Variable	Definition
Participation	Reported households decision to participate in health insurance; = 1 when answered yes to participation and 0 otherwise
Need	The household's self-assessed health and described as (1) Good (2) Fairly Good (3) Not so Good (4) Poor. This was collapsed into a binary variable that takes 1 if the household's health status is (3) and (4) and 0 otherwise. A household therefore needs health insurance if her health status is generally not good.
Cost	Attribute that defines the amount to be paid for the health insurance scheme and they are SLL 4000, 6000 & 10000
Coverage	Attribute that defines the benefit of the scheme and are Simple, Moderate & Comprehensive. Moderate coverage is used as the definition of coverage
Waiting Time	Attribute that shows the time to wait to see a doctor/nurse and are 45, 60 and 90 minutes
Public Provider	Attribute that shows one of the type of providers a member of the scheme can visit; = 1 when visited and 0 otherwise
Non Public Provider	Attribute that shows a type of provider a member of the scheme can visit; = 1 when visited and 0 otherwise
FCP	Calculated household's financial capacity to pay for health insurance and it is continuous
Corruption	Reported households perception of corruption in the health sector; = 1 when reported corrupt and 0 otherwise
Petty Trading	Reported type of informal sector = 1; 0 otherwise
Subsistence Farming	Reported type of informal sector = 1; 0 otherwise
'Okada'	Reported type of informal sector = 1; 0 otherwise
Cattle Rearing	Reported type of informal sector = 1; 0 otherwise
Fishing	Reported type of informal sector = 1; 0 otherwise
Tailoring	Reported type of informal sector = 1; 0 otherwise
Mining	Reported type of informal sector = 1; 0 otherwise
Quarrying	Reported type of informal sector = 1; 0 otherwise
School	Reported whether household went to school; yes = 1; 0 otherwise
Distance to HC	Reported distance from village to nearest health centre
Age of Household Head	Reported age of head of the household
Shock	Reported shock to household's main informal economic activity; yes = 1; 0 otherwise
Household Size	Number of members in the household as at the time of the interview
Remittance	Household receives remittance; yes = 1; 0 otherwise
Diseases	Any household member has suffered from malaria or typhoid fever over the past 3 months prior to interview; yes = 1; 0 otherwise
Expenditure	Total household monthly expenditure
Location	Household location; Rural or Urban
Smoke/Drink	Household head or any member smokes/Drinks; yes = 1; 0 otherwise

5.3.4 Data and Summary Statistics

Table 5.3 presents the descriptive statistics for all variables used in the analysis based on the perceived need for health insurance. For each variable, the means for those households that perceived need for health insurance (NEED) and those that did not are shown, as are their mean differences, standard errors and statistical significance. Overall, these results show that the distribution of the health insurance scheme and household characteristics varies between households that perceive NEED and those that do not perceive NEED.

Table 5.3 shows that the mean differences between households which perceived a need for health insurance and those which did not are in some cases small, whereas in other cases the differences are wide and significant. Due to the large sample, there are statistically significant differences between households which perceived a need for health insurance and those which did not, in all samples except where the household is in petty trading, subsistence farming, cattle rearing, or quarrying, and the age of the household head.

Table 5.3: Sample Means by Perceived Need-Independent Variables

Variables	Households' Perceive NEED (N = 10593)	Households' Do Not Perceive NEED (N = 15651)	Mean Difference (NEED-No NEED)	Standard Error
Cost	6412.914	6838.413	-425.4987	31.27501***
Coverage[1]	1.165392	0.8880583	0.277334	0.0101295***
Waiting Time	63.60096	65.9469	-2.345941	0.234925***
Public Provider	0.2744265	0.373203	-0.0987765	0.0058998***
Non Public Provider	0.4610592	0.2468852	0.214174	0.005782***
FCP	272368.9	277689.4	-5320.441	1100.713***
Corruption	0.9065421	0.8918919	0.0146502	0.0038101***
Petty Trading	0.2728217	0.2673312	0.0054905	0.0055829
Subsistence Farming	0.1929576	0.2006262	-0.0076685	0.0050091
'Okada'	0.240253	0.2134688	0.0267842	0.0052455***
Cattle Rearing	0.0484282	0.0500288	-0.0016005	0.0027261
Fishing	0.057774	0.0920069	-0.0342329	0.0033713***
Tailoring	0.1163976	0.0971823	0.0192153	0.0038542***
Mining	0.0331351	0.039678	-0.0065429	0.0023758***
Quarrying	0.0382328	0.039678	-0.0014452	0.0024386
School	0.7153781	0.6474986	0.0678795	0.0058787***
Distance to HC	2.216155	2.093235	0.1229209	0.0326117***
Age of Household Head	43.57009	43.51121	0.0588801	0.16676
Shock	0.4892854	0.4658488	0.023465	0.0062817***
Household Size	5.011045	5.06843	-0.0573851	0.0292615**
Remittance	0.1546304	0.173663	-0.0190326	0.0046798***
Diseases	0.8768054	0.6382979	0.02385076	0.0053571***
Expenditure	368431.9	375564.1	-7132.164	1471.13***
Location	0.347588	0.3110983	0.0364897	0.0058927***
Smoke	0.2525253	0.1303431	0.1221821	0.004711***

*****p <0.01; **p<0.05; *p<0.1; 1. Moderate coverage used here for coverage**

For instance, households that do not perceive NEED are on average more likely to have FCP, are less likely to pay for free health care (corruption), be less educated, be close to the nearest health centre, have more members in their households, and receive more income and spend more than households who perceive NEED. Households who perceive NEED are typically located in urban areas, have a head of household who smokes, suffer from diseases such as malaria and typhoid more often, have an older head of household, suffer more from shocks, and be more likely to pay for free health care (corruption) than their counterparts in households that do not perceive NEED. To put this into perspective, the mean number of household heads who smoke is significantly more by 48.4% than households where the head does not perceive NEED. In terms of education of the household head, for households, who perceived NEED, the heads are about 10% better educated than their counterparts. Households, who do perceive NEED, are about 2% less likely to have the financial capacity to pay for health insurance because this category of households on average spends more than their counterparts.

5.4 ECONOMETRIC MODELS AND EXPLANATORY VARIABLES

5.4.1 Model Development

This paper attempts to investigate how ATP is associated with participation in health insurance, controlling for household characteristics and health insurance attributes. With this mind, it uses a modified Bundorf and Pauly (2006) model of health insurance by which:

$$U_{ij} = f(\beta A_{ij}, \gamma H_i) + \varepsilon_{ij} \qquad (5.1)$$

where U_{ij} is the utility household *i* expects to get from choosing health insurance *j*; *j* is the health insurance scheme; A is a vector of the health insurance attributes; H is a vector of the household's socio-economic characteristics and ε the error term; β and γ are vectors of coefficients to be estimated.[61] From Equation 5.1, the unexplained component ε_{ij} captures the unobserved variation in the characteristics of different options. Since the random component is unobservable in choice, an individual's choice is therefore probabilistic rather than deterministic.

Let Y_i be a random variable that indicates the choice made. Given the choice made between two alternatives *j* and *k*, the probability that household *i* will choose alternative *j* is thus given by:

$$\text{Prob } (Y_i = j) = \text{Prob } (U_{ij} - U_{ik})$$

$$\text{Prob } (V_{ij} - \varepsilon_{ij} > V_{ik} - \varepsilon_{ik}) \ \forall\, j \neq k; \quad \text{or}$$

$$\text{Prob } (V_{ij} - V_{ik}) > \text{Prob } (\varepsilon_{ij} - \varepsilon_{ik}) \qquad (5.2)$$

Equation 5.2 is developed from the basic assumption that household *i* will choose alternative *j* if and only if alternative *j* maximises their utility given alternatives *j* and *k* in the choice set.

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[61] The study follows not only the model of Bundorf and Pauly (2002) but also that of Bradley (2009) and Jutting (2003)

If however the error terms in Equations 5.1 and 5.2 are assumed to be independent and identically distributed (IID) extreme values, then an analytical solution does exist. Therefore the probability of household i participating in health insurance scheme j is given by the following probit function:

$$P_{ij} = \frac{e^{\left(\beta A_{ij} + \gamma H_i\right)}}{1+e^{\left(\beta A_{ij} + \gamma H_i\right)}} \tag{5.3}$$

where A and H are vectors of explanatory variables of attributes of the scheme and households' characteristics respectively; and β & γ are vectors of coefficients to be estimated.

5.4.2 Econometric Analysis

5.4.2.1 Introducing ATP and Need for Health Insurance

It is assumed that participation in health insurance depends on ATP and the perceived need for health insurance. Ability to Pay (ATP) for health insurance depends on whether or not a household needs health insurance and whether it can afford to pay for it. In this study an affordability threshold as the households' Financial Capacity to Pay (FCP) for health insurance is defined.[62] In order to determine whether households have the ability to pay for health insurance, the relationship between perceived need and participation in health insurance must be examined.

The decision as to whether a household perceives a need for health insurance is not random but is determined by whether there is a need based on their characteristics, which may or may not be directly observed in the data. For instance, households, who live in a cleaner environment which impacts positively on their health, may be less likely to perceive a need for health insurance. Those that live in a hazardous environment which impacts negatively on health may strongly perceive a need for health insurance. This selection problem can be addressed by controlling for observed and unobserved characteristics.

The empirical work we develop here is based on the assumption that households' decisions to participate in health insurance (PART) depends on their perceived need (NEED), their financial capacity to pay (FCP) for health insurance, and other observable household and specific health insurance scheme characteristics. When modelling NEED as having an impact on PART, NEED is first assumed to be first exogenous (not correlated with the error term) and then endogenous in the PART equation.

Assuming that latent (true) NEED depends on household characteristics (H_n) such that as can be expressed:

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[62] The definition and construction of FCP as the affordability threshold is discussed in a subsequent section of this paper.

$$\text{NEED}_i^* = \gamma_i \text{H}_{\mathbf{ni}} + \mu_{\text{ni}} \tag{5.4}$$

where NEED_i^* is need for health insurance by household *i*; H is the household characteristics that affect perceived need for health insurance; γ_i is the vector of coefficients; and μ_i is the error term. The observed variable NEED_i, is a dichotomous decision variable which takes the value 1 when NEED is observed and 0 otherwise, such that $\text{NEED}_i = 1$. Assuming a normal distribution, [μ_{ni} ~ N (0,1)], the value can be estimated in the model using a probit method:

$$\text{P}(\text{NEED}_i = 1) = \text{P}(\text{NEED}_i^* > 0) = \text{P}(\gamma\text{H}_{\text{ni}} + \mu_i > 0) = \emptyset(\text{H}'_{\text{ni}}\gamma) \tag{5.5}$$

Equally, supposing that the household's true (latent) propensity to participate in a health insurance scheme (PART) depends on the attributes of the scheme (A), then the true household revealed perceived need (NEED), and households' characteristics - (H_p) (including FCP and NEED*FCP). The latent variable PART is modelled as shown below:

$$\text{PART}_{ij}^* = \beta\text{A}_{ij} + \eta\text{NEED}_i + \gamma_i\text{H}_{\text{pi}} + \mu_{ij} \tag{5.6}$$

where A_{ij} refers to attributes of health insurance scheme *j* as chosen by household *i* and β, η, and γ represent coefficients of the attributes of the health insurance scheme (A), NEED and households' characteristics (H_p) respectively. [63] The error term is assumed to be a normally distributed random variable. Since PART_{ij}^* is latent, a dichotomous decision is defined as variable PART_{ij} which takes the value 1 when the household answers it will participate in the health insurance scheme and 0 otherwise. Equally, participation in a health insurance scheme is estimated using a probit model:

$$\text{P}(\text{PART}_{ij} = 1) = \text{P}(\text{PART}_{ij}^* > 0) = \text{P}(\beta\text{A}_{ij} + \eta\text{NEED}_i + \gamma_i\text{H}_{\text{pi}} + \mu_{ij} > 0)$$
$$= \emptyset(\beta\text{A}_{ij} + \eta\text{NEED}_i + \gamma_i\text{H}_{\text{pi}}) \tag{5.7}$$

The results of Equation 5.7 may be biased because of the possible endogeneity of NEED in the model. This may be due to unobserved household heterogeneity simultaneously driving PART and NEED outcomes. Since NEED and PART are simultaneously determined, and NEED is endogenous, there are some unobserved sources of variation across households that are not readily captured by the covariates.

There are several methods used to circumvent these problems and this paper uses the following approaches: a naïve univariate probit model and a Recursive Bivariate Probit Model (RBPM) approach wherein it is assumed that the error terms in Equations 5.5 and 5.7 are correlated, hence NEED is treated as endogenous in Equation 5.7.

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[63] At this stage just the general model of participation in health insurance is presented. All household characteristics including the interaction terms are embedded in the variable H.

5.4.2.2 Naïve Univariate Probit Model

As defined in Equation 5.6, PART is a linear function of NEED, A, FCP and H (including the interaction term NEED*FCP), which can be estimated using a univariate probit model.

To estimate the naive probit method, it is assumed that the error terms in Equations 5.4 and 5.6 are uncorrelated, hence treating the need for health insurance as exogenous. The naive univariate probit model serves, as a basis for evaluating the extent to which the estimate of the impact of NEED on PART is sensitive to the assumption that NEED is exogenous. It serves as the baseline model for the models and the results present the marginal effect of NEED, and of other variables on PART, in a simple probit model. The model conditions on a set of health insurance scheme attributes (A), FCP, household characteristics (H) and NEED, FCP*NEED which are explained later on.

5.4.2.3 Correcting for Endogeneity of NEED

Selection of unobservables takes into consideration the random and unobservable household characteristics that influence treatment (NEED) and are associated with the outcome (PART). Given the structure of the data used in the empirical analysis, the models of NEED (Equations 5.4 and 5.5) and PART (Equations 5.6 and 5.7) comprise a dichotomous dependent variable (PART) and a potentially endogenous dichotomous regressor (NEED).

For the naïve model, it is assumed that NEED conditional on the covariates is independent of PART. If, however, NEED is endogenous, then the Conditional Independence Assumption (CIA) is violated and the estimates from the univariate probit model are biased and unreliable.[64] Several alternative methods can be used to address the issue of endogeneity of NEED in the PART equation and the binary nature of both perceived need and participation variables. Since there is no clear consensus in the econometrics literature concerning an acceptable method for solving endogeneity, and to test and control for the endogeneity of NEED, this study makes use of the RBPM with and without an exclusion restriction.

5.4.2.4 The Recursive Bivariate Probit Method (RBPM)

The random error terms in Equations 5.4 and 5.6 are assumed to follow the bivariate normal distribution that assumes that two endogenous dummy variables may not coexist in mutual functional relations. The endogenous variable (NEED) and the outcome variable (PART) are both

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[64] Also called unconfoundedness or selection on observables, states that conditional on covariates X, the assignment of study participants to binary treatment conditions (i.e. treatment vs. nontreatment) is independent of the outcome of nontreatment and the outcome of treatment (Guo & Fraser 2015, pp. 29).

binary and, as Greene (2008) suggests, when the endogenous variable in a probit model is binary, a RBPM is appropriate.[65]

Given Equations 5.4 and 5.6, and following Greene (2003):

$$\mathrm{NEED}_i^* = \gamma_i \mathrm{H}_{ni} + \mu_{ni} \quad \mathrm{NEED}_i = 1 \text{ if } \mathrm{NEED}_i^* > 0, 0 \; otherwise \tag{5.8}$$

$$\mathrm{PART}_{ij}^* = \beta \mathrm{A}_{ij} + \eta \mathrm{NEED}_i + \gamma_i \mathrm{H}_{pi} + \lambda\left(NEED_i * FCP_{ij}\right) + \mu_{pij}$$

$$\mathrm{PART}_{ij} = 1 \text{ if } \mathrm{PART}_{ij}^* > 0, 0 \; otherwise \qquad (5.9)^{66}$$

$$\mathrm{E}(\mathrm{NEED}_i) = \mathrm{E}\left(\mathrm{PART}_{ij}\right) = 0; \qquad \mathrm{Var}(\mathrm{NEED}_i) = \mathrm{Var}\left(\mathrm{PART}_{ij}\right) = 1;$$

$$\mathrm{Cov}\left(\mathrm{NEED}_i, \mathrm{PART}_{ij}\right) = \rho;$$

where subscripts *n*, *p*, *i* and *j* represent need, participation, the household and choice made respectively; NEED_i^* is a latent variable representing household i's need for health insurance; PART_{ij}^* is a latent variable representing household *i* participating in health insurance scheme *j*; γ and β are vectors of model coefficients associated with the explanatory variables H_i and A_{ij}; and η is a scalar coefficient for NEED_i to measure the impact of need for health insurance on a household participating in health insurance scheme *j*. The RBPM (Equations 5.8 and 5.9) is without the exclusion criterion.

The correlation between the two error terms μ_{ni} and μ_{pij} stems from variables affecting the probability of NEED and the probability of PART, which are not observable. The study assumed that these disturbance terms comprise two components: (1) unobserved household heterogeneity (ϑ_i); and (ii) a constant part unique to each model (ε_{ni} and ε_{pij} respectively).

$$\mu_{ni} = \vartheta_i + \epsilon_{ni}$$

$$\mu_{pij} = \vartheta_i + \epsilon_{pij} \tag{5.10}$$

If ρ = 0, then the bivariate probit is equivalent to two independent probit models.

As a way of solving this problem of endogeneity, the study used a recursive bivariate probit model approach to detect the presence of endogeneity by testing if the cross-equation correlation between the PART equation and the identification equation is significantly different from zero. The bivariate probit model is recursive because the outcome variable, PART depends on the exogenous variables A_{ij}, $\mathrm{FCP}_i, \mathrm{H}_{pi}$ and NEED_i. The equation for NEED is therefore a reduced form, which depends on the vector of exogenous variables, FCP_i and H_i. The outcome equation

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65 Some authors use RBPM as an IV method such as Morris (2007) and Humphreys *et al.* (2011).

66 The impact of FCP on PART might vary by perceived NEED, hence to allow this possibility, the interaction of FCP and NEED to the PART equation were added.

(PART) is a structural equation, which depends on the vector of exogenous variables, $\mathrm{A_{ij}}$, $\mathrm{FCP_i}$, $\mathrm{H_{pi}}$ and the endogenous variable need for health insurance, ($\mathrm{NEED_i}$).

From Equations 5.9 and 5.10, ρ is the correlation coefficient between the error terms in the said equations that measures the correlation between perceived need and participation once the explanatory variables have been factored out. According to Wooldridge (2002), a likelihood ratio test of the significance of ρ is a direct test of endogeneity of $\mathrm{NEED_i}$ and $\mathrm{PART_{ij}}$. If ρ = 0, then the bivariate probit model is equivalent to individual probit models. If ρ is not zero then the variables need and participation are endogenous, the univariate probit results are biased, therefore allowing use of the RBPM.

In order for the parameters in Equations 5.9 and 5.10 to be consistently estimated, the system must be identified. Exclusion restrictions serve the same purpose and must fulfil the same key characteristics as instrumental variables in a linear setting. As Angrist *et al.* (1996) explained, they must be highly correlated with the treatment indicator and be orthogonal to the error term in the outcome equation. The conditions for such identification are that an explanatory variable must appear in the NEED equation that does not appear in the PART equation and that a regressor in PART_{ij}^{*} that affects NEED but does not affect PART is excluded. To improve identification, an exclusion restriction on the participating equation is imposed. Maddala (1983) argued that the parameters of the participation Equation (5.10) are not identified if there are no exclusion restrictions. Jones *et al.* (2006) described that as common practice, even though identification relies strongly on bivariate normality assumption, there is a need to impose exclusion restrictions to improve identification in the RBPM. In this thesis the health behaviour of the household head is used as the exclusion restriction. Health behaviour of the household head is a dummy variable that takes the value 1 if the household head smokes or drinks alcohol, or 0 otherwise. It is widely supported in the literature that smoking and drinking alcohol impacts negatively on health, which is a direct measure of NEED, and hence they are correlated. It is believed to only impact PART through influencing NEED.

The RBPM (with exclusion restriction) for the analysis of need and participation in a health insurance scheme are given below:

$$NEED_i^{*} = \gamma_1 H\ Characteristics'_{ni} + \mu_i, NEED = 1\ if\ NEED^{*} > 0 \tag{5.11}$$

$$PART_{ij}^{*} = \beta_i A_{ij} + \eta_i NEED_i + \alpha_{ij} FCP_{ij} + \gamma_i H_{pi} + HB_{ni} + \lambda(\mathrm{Need} * \mathrm{FCP}) + \mu_{ij},$$

$$PART = 1\ if\ PART^{*} > 0,\ \left(\begin{matrix}\mu_1\\ \mu_2\end{matrix} \middle| H_{ni} H_{pi}\right) \sim N\left\{\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}\right\} \tag{5.12}$$

where the variables are defined as shown earlier. FCP is defined following the work of Xu (2005) who concluded that the subsistence expenditure of a household is estimated based on:

$$FCP_i = Cexp_i - Sexp_i$$
$$Sexp_i = fpl * eqsize_i$$
$$eqsize_i = \text{hh}size_i^{\partial} \quad (5.13)$$

where $Sexp_i$ is household i's subsistence expenditure and $Cexp_i$ is consumption expenditure, which is used here as the household's total expenditure. This is because poor informal sector households do not have the ability to save from their income; fpl is the national food poverty line; and $eqsize_i$ is the equivalent household size; hh$size_i$ is the household size for household i; and ∂ is a constant of 0.56. The poverty line used here is the food poverty line of Sierra Leone in 2009. Xu (2005) defines the household's subsistence expenditure as the basic requirements needed to maintain a household's starting point in life.

The recursive bivariate probit model is estimated using the bivariate command (biprobit) with robust standard errors using STATA/SE13. This command uses the maximum likelihood method to estimate the model.

The RBPM approach is common within the health economics literature and a non-exhaustive list of its application in health economics includes the following studies: Costa-Font and Jofre-Bonet (2008); Chen *et al*. (2013); Buchmueller *et al.* (2005); Gitto *et al*. (2006); Costa-Font and Gil (2005); Latif (2009); Goldman *et al*. (2001); and Morris (2007). One aspect that is common to all these examples is, as Marra and Radice (2011) put it, the presence of unmeasured factors that influence the binary outcome, which are likely to be correlated with the binary treatment.

5.5 RESULTS

A total of 1,458 households' data is used in this study, culminating in 26,244 observations; that is, 1,458 households each choosing from 9 discrete-choice experiment scenarios with two alternatives. Data from the DCE survey and socio-economic characteristics of households form the mainstay of the data used for the analysis.

5.5.1 REGRESSION RESULTS

Table 5.4 below presents the estimation results of NEED and PART using different estimation methods as highlighted earlier. The main results that compare all the methods used are shown in Tables 5.4 and 5.5 and in the following subsections. Column A of Table 5.4 present results of the naive univariate probit model for the variable PART with the assumption that the variable NEED is exogenous. Column B presents the results of the PSM - IV probit model that corrects for endogeneity of the variable NEED. Columns C & D present results of the recursive bivariate probit model that corrects for endogeneity and the fact that NEED is binary. Table 5.4 also presents the regression results for the four empirical models. Marginal effects are estimated in this work and all results are reported in terms of marginal effects.

Table 5.4: Marginal Effects-Participation and Need (Full Sample)

	Probit Model (A)	Recursive Bivariate Probit Model (Without Exclusion Restriction Satisfied) (B)		Recursive Bivariate Probit Model (With Exclusion Restriction Satisfied) (C)	
Variable	**Participation (se)**	**Participation (se)**	**Need (se)**	**Participation (se)**	**Need (se)**
Cost	-9.45e-06 (1.46e-06)***	-2.40e-07 (0.00000)**		-3.11e-07 (0.0000)**	
Coverage	0.07421 (0.0065)***	0.00186 (0.0009)**		0.00253 (0.00096)***	
Waiting Time	-0.00074 (0.00018)***	-0.00002 (0.00001)*		-0.00003 (0.00001)**	
Public Provider	-0.00038 (0.00784)	-0.00023 (0.00022)		-0.00052 (0.00033)	
Contracted/Non Public Provider	0.10583 (0.0107)***	0.0023 (0.00116)**		0.003 (0.00122)**	
Ln (FCP)	0.05356 (0.01033)***	0.00168 (0.00081)**		0.00221 (0.00088)**	
Corruption	-0.02828 (0.00693)***	-0.00504 (0.0004)*		-0.00078 (0.0004)*	
Petty Trading			0.02469 (0.00679)***		0.01402 (0.00752)*
Subsistence Farming			0.00578 (0.00767)		0.02203 (0.00834)***
'Okada'			0.05154 (0.00702)***		0.04168 (0.0079)***
Fishing			-0.06263 (0.0101)***		-0.07705 (0.01037)***
Tailoring			0.063 (0.00784)***		0.05482 (0.009)***
Distance H Centre			0.00633 (0.00076)***		0.00921 (0.00087)***
Basic Education[2]			0.08115 (0.00501)***		0.07587 (0.00546)***
Age			0.00175 (0.00018)***		0.00194 (0.00021)***
Health Behaviour					0.16976 (0.0071)***
NEED	0.999998 (6.71e-06)***	0.35768 (0.04694)***		0.39117 (0.024)***	
NEED*Ln (FCP)	-0.19877 (0.06431)***	-0.00504 (0.00298)*		-0.00781 (0.00431)*	
No of Observation	26244	26244		26244	
Wald Chi2 (k-1)	1163.80	742.02		1231.01	
Prob >Chi2 (k-1)	0.0000	0.0000		0.0000	
Log Pseudolikelihood	-6597.8072	-23946.328		-23535.942	
R2	0.6373				
Rho		0.9695321		0.9452251	
(se)		(0.0077802)		(0.0085401)	
Wald test rho=0 Chi2(k-1)		258.468		495.939	
Prob > chi2		0.0000		0.0000	

***p < 0.01; **p < 0.05; *p < 0.1; 1 = the baseline informal sector activities used were cattle rearing, mining and quarrying due to their small sample size; 2 = the reference variable used is No Education, i.e. the household head did not go to school

5.5.1.1 The Univariate Probit Model

The results for the univariate probit model are shown in column A of table 5.4. The result shows the direct effect of NEED, the attributes of the health insurance scheme, the affordability threshold (FCP), corruption, and the joint impact of NEED and FCP on participating in the health insurance scheme. It does not control for endogeneity. However, before estimating the univariate probit model, a two-step model is estimated and from the two-step regression result, the ensuing univariate probit model assumed that NEED is an exogenous regressor in the PART equation (see Appendix A for the result of the two-step model). This is to evaluate the extent to which the results are sensitive to the assumption that NEED is exogenous.

The results are presented in terms of marginal effects, standard errors and statistical significance of the variables in the single probit model. The variables have the required sign; for instance, corruption is expected to be negative because it can discourage households from participating in health insurance schemes. Evaluated at the sample mean of the regressors, the attributes, coverage and non-public provider significantly increase the probability of PART by 7.4 and 10.6 percentage points respectively. The affordability threshold variable, FCP, significantly increased the probability of participation in health insurance. Cost, waiting time and corruption significantly decreased the probability of participation. The need for health insurance significantly increased participation in health insurance by almost 100 percentage points. However, the joint effect of Need and FCP on PART significantly decreased PART.

In summary, the results show that the likelihood of a household participating in the hypothetical health insurance scheme decreases with the cost of the scheme, waiting time, having a public provider, and corruption. However, it increases when there is an improvement in coverage, improvement in a households' FCP, having a non-public provider, and a perceived need for health insurance. The higher a household's FCP and perceived need for health insurance, the more likely the households will want to participate in the said scheme.

5.5.1.2 Recursive Bivariate Probit Model

Results of the recursive bivariate probit model are reported in columns B and C of Table 5.4. Two results of the recursive bivariate probit model are reported; one that satisfies the exclusion restriction (the variable used is the health behaviour variable measured by whether any member of the household drinks/smokes or not) and the other that did not. The recursive bivariate probit model does control for the endogeneity of NEED in the PART equation.

The resulting output includes a test for the null hypothesis of exogeneity that H_0: $\rho = 0$. The Wald test of $\rho = 0$ is 258.5 and 495.9 for both recursive models and the probability > chi2 is 0.0000, suggesting the hypothesis is rejected; ρ is significant, positive and significantly different from zero at the conventional 5% for PART. The results of the RBPMs suggest that with high probability, NEED and PART are endogenously determined. This implies that the results from the univariate probit model are biased, and that the recursive bivariate probit models are more appropriate. The positive values of ρ in the recursive models also imply that the unexplained factors that affect NEED are positively correlated with unexplained factors that affect PART.

From the recursive model with exclusion restrictions in column C, it can be seen that the variables NEED, coverage, and non-public provider significantly increase the likelihood of participation in health insurance by 35.8, 0.19, and 0.23 percentage points, respectively. Corruption and public choice of provider decrease PART by 0.5 and 0.02 percentage points respectively. FCP significantly increases the probability of PART while the cost of the scheme and waiting time significantly decreases PART. An increase in FCP by 1SLL will increase the expected probability of PART by 452.5 points. An increase in cost and the joint effect of NEED*FCP by 1SLL will decrease PART by 32,154.3 and 128 points respectively. The interaction term NEED*FCP captures the differential effect of income (affordability threshold) on those households that perceives NEED.

The probability of participation in health insurance therefore increases with an improvement in coverage, having a non-public provider, NEED for health insurance, and an increase in households' FCP for health insurance. The results also show that NEED is the most significant variable and influences PART greatly.

The variable 'health behaviour' is used as an exclusion restriction variable, and its primary objective is to improve the model, as is evidenced by the results for the RBPM with exclusion restriction satisfied. Comparing both RBPMs, the coefficients are fairly larger for the RBPM with exclusion restriction but the signs of the variables are the same. For instance, the coefficients of the variables, NEED and FCP are larger by about 8.6% and 24% in the model with restriction than the model without, but the signs of the variables are the same.

After accounting for the endogenous nature of perceived NEED, its effect diminishes significantly. In Table 5.4, the marginal effect of the variable NEED for the univariate naive probit model is 0.99. However, after controlling for endogeneity, the RBPMs show that the magnitude of impact of the marginal effect of perceived NEED diminishes considerably from 0.99 in the univariate probit model to 0.36 and 0.39 (63.9% and 60.5%) for RBPM with and without the exclusion restriction respectively. The implication is that a household that perceives a need for health insurance can positively and significantly impact their participation in health insurance. However, after correcting for endogeneity, the RBPM reduces this impact by a considerable figure. After controlling for endogeneity, the results also indicate that it is possible that there are omitted variables that are positively correlated with both perceived need and participation. For instance, households' feeding habits: how often do they eat per day and whether or not the food is balanced could influence NEED and PART since poor feeding habits can affect one's health, a sign of NEED, and will end up impacting positively on PART.

Table 5.5: Ability to Pay - Using all Models

Variables	Univariate Probit Column A	RBPM (Exclusion Restriction not Satisfied) Column B	RBPM (With Exclusion Restriction Satisfied) Column C
Need	0.999998	0.35768	0.39117
	(6.71e-06)***	(0.04694)***	(0.024)***
FCP	0.05356	0.00168	0.00221
	(0.01033)***	(0.00081)**	(0.00088)**
NEED*FCP	-0.19877	-0.00504	-0.00781
	(0.06431)***	(0.00298)*	(0.00431)*
No of Observations	26244	26244	26244
Wald Chi2 (k-1)	1163.80	742.02	1231.01
Prob >Chi2 (k-1)	0.0000	0.0000	0.0000
Log Pseudolikelihood	-6597.8072	-23946.328	-23535.942
R2	0.6373		
Rho		0.9695321	0.9452251
(se)		(0.0077802)	(0.0085401)
Wald test rho=0 Chi2 (k-1)		258.468	495.939
Prob > chi2		0.0000	0.0000

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; The PS Matching result is the ATT

Our results show that the variables NEED and FCP positively influence the likelihood of PART in the health insurance scheme.

The implication of NEED*FCP for ATP is that households that perceived NEED do not have the ability to pay for health insurance and hence, are less likely to participate in the scheme. Recent studies (Dong *et al.,* 2009; Atinga *et al.,* 2015; and Kusi *et al.,* 2015) show that affordability or ATP is the singular most important reason why insured individuals are dropping out of health insurance schemes.

5.6 DISCUSSION AND CONCLUSION

This study addresses whether informal sector households in Northern and Western Sierra Leone can afford to pay for health insurance. Economists have most often come up with three possible answers: that the decision not to participate in health insurance can result from low income relative to the high cost of health care; that there is a low perceived demand for health care; and that varying consumer preferences for income protection or their degree of risk aversion. Policy makers see these as problems of affordability, making them seek a practical solution to this issue. This is the same line of reasoning adopted in this paper, seeking a practical answer to the problem of affordability of health insurance in Sierra Leone. This study uses the behavioural (what households actually buy) as opposed to the normative (what households could buy) definition of affordability.

This study looked at ATP for health insurance using the DCE methodology. It differs from other ATP studies in several ways. First, it includes two main components of ATP for health insurance in its analysis, and looks at perceive need and participation in health insurance independently and jointly. Second, it includes perceived need in the participation in health insurance model as need is a prerequisite for participation in health insurance. So far as the authors are aware, this is the first paper to incorporate FCP for health insurance in an ATP study and it is the first to look at ATP for health insurance using DCE methodology. This is also the first study on Sierra Leone to produce estimates that control for endogeneity of perceived need and participation in health insurance using a recursive bivariate probit model, with and without exclusion restrictions. It shows that perceived need is endogenously determined with participation in health insurance and that the results hinge on this. Finally, since perceived need is considered a prerequisite for participation in health insurance, it estimated them jointly. However, need for health insurance is used as an explanatory variable in determining participation in health insurance. This therefore calls for estimating both equations through the use of an RBPM.

The univariate probit model is a reduced form equation; hence the results are suggestive of an association between perceived need and participation. Inasmuch as the univariate probit model exhibits a significant positive effect of perceived NEED on PART, it overestimates the magnitude of the impact, as shown when correcting for endogeneity issues.

Results from the RBPM (which is the main model in this study) show that households who perceived a need for health insurance also had a strong desire to participate in the health insurance scheme. The positive and significant effects of the endogenous regressor NEED support this statement. However, the joint effect of NEED*FCP is first estimated to first show the differential effects of income (FCP) on those households who perceive NEED and secondly to estimate ATP.

A positive coefficient of NEED*FCP shows two effects: first that households have the ATP for health insurance; and second, that households who perceived NEED and have the ability to pay are more likely to participate in the scheme. All the models used conclude that households in the sample do not have the ability to pay for health insurance and also that households who have a NEED and could not afford to pay are less likely to participate in the scheme as shown by the negative coefficient of NEED*FCP.

Overall, the findings in this study demonstrate that NEED has a positive impact on PART. This finding is in line with similar studies. For instance, a study by Wang and Rosenman (2007) on rural Chinese residents concludes that perceive need impacts positively on health insurance purchases. Another study by Oriakhi and Onemolease (2012) concludes that medical expenses positively and significantly impact on participation in community based health insurance schemes. This result supports the findings of Wang *et al.* (2005) that rural individuals join health insurance schemes to reduce the costs incurred during sickness. The overall implication is that the more people get sick (a definition for Need), the higher their medical expenses and the more they will be willing to participate in a health insurance scheme to reduce their overall medical costs. This is likely to arise owing to the fact that before households participate in a health insurance program, they must perceive a need for it. Another finding from the study is that NEED*FCP has a negative impact on PART in all methods used. To support this point, a study by Dong *et al.* (2009) highlighted inability to pay and health needs as main reasons why households drop out from CBHI schemes in Burkina Faso. They also found out that about one-third of households sampled gave unaffordability as the main reason for them to drop out of the scheme. They concluded that participation in health insurance schemes for informal sector workers is influenced mainly by affordability and need.

The empirical analysis of this study suggests that not taking endogeneity of the variable NEED into consideration could result in an overestimate of the impact of NEED on PART. Taking into consideration the marginal effects of the components of ATP (NEED, FCP, and NEED*FCP), these results show upward bias for the naïve univariate probit model that do not control for endogeneity. For those methods that do control for endogeneity, the results show that the marginal effects of the ATP components are smaller.

There are some caveats to this study. First, part of the data we generate is using the DCE, which limits the number of variables to the number of choice scenarios, a total of 18. Second, it is possible is the that the income data might have suffered from memory loss as not all households could remember their monthly income exactly for non-paid jobs like the majority of jobs in the informal sector. The third limitation is that the study does not cover the whole of Sierra Leone but focuses on only two regions, the northern and western regions. The choice of these two areas is deliberate; the north has the poorest district while the western area is the richest region in the country. Deaton and Paxson (1997) argued that the choice of study area when purposively driven by the researcher's prior knowledge and familiarity enhances the accuracy of the data to be obtained, at least to a degree, and the econometric estimates obtained thereof.

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Chapter 6 – Conclusions and Recommendations

6.1 INTRODUCTION

In this thesis, we have reviewed the literature on the application of DCE to WTP for health outcomes; we have examined willingness to pay (WTP) for health insurance, the impact of corruption on a household's decision to participate in health insurance, and ability to pay (ATP) for health insurance with special reference to the informal sector in Sierra Leone. The aim of the thesis was to provide rigorous and quantitative analysis of willingness and ability to pay for health insurance among informal sector workers in the northern and western region of Sierra Leone. We noticed from the onset that determining households' WTP is incomplete without determining whether households have the financial capability to pay for health insurance.

To meet the general aim of this thesis and answer the research questions therein, the chapters (chapters 2 – 5) of this thesis have provided a detailed analysis of willingness and ability to pay for health insurance. This thesis therefore comprised four studies (stand alone papers) that focused on the following: the discrete choice methodology, WTP for health insurance, impact of corruption on participation in health insurance, and ATP for health insurance.

Chapter 2 provided a comprehensive literature review of the application of discrete choice experiment (DCE) method to WTP for health outcomes in health economics. Chapter 3 on the other hand presented an empirical analysis of WTP for health insurance among informal sector workers in Sierra Leone using the DCE method. Chapter 4 looked at the impact of corruption on informal sector households' participation in health insurance. Chapter 5 finally looked at ATP for health insurance among informal sector households in Sierra Leone.

In this last and final chapter, we summarized earlier findings from the various papers and discussed policy implications. Part of this chapter also, we present contributions made and the limitations of the entire study. Finally, we propose some policy recommendations.

6.2 MAIN FINDINGS

In chapter 2, we did a systematic literature review on the application of DCEs to WTP studies for the period 1990 – 2013. Our result shows that from 1990 – 2013 inclusive, a total of 199 published health economics articles have used the DCE method to estimate WTP. We observed that the number of published articles have increased over the years. Take for instance, from 2001 – 2010, a total of 106 articles were published whereas from 2011 – 2013, a total of 79 articles were published already. For the entire period of the review, about one-fourth of the studies were carried out in the UK, which was the highest. The objectives, WTP, economic evaluation and health states, patient-physician relationship and preferences, and human resource issues are the most widely studied areas for the period reviewed.

Outside the monetary measure, which is used to determine WTP, staff welfare, time and health status domain are the most widely used attributes. On the number of attributes used, from 4 – 6 attributes used dominated the literature, whereas 9 – 16 choice sets are the most widely used choice sets in the literature. However, this is in line with theory, as the number of choice sets increased, the more it becomes difficult for respondents to comprehend. In terms of the method used to create choice sets, orthogonal arrays continue to dominate the literature. Our study also found that about 51% of the articles reviewed used orthogonal arrays in designing their experiments. Fractional factorial designs are the most popular type of design used and our review shows that 61% of the studies used it. The use of software in generating experimental designs continues to dominate the literature. From our review, about 55% of the literature reviewed used software to generate experimental designs and SAS is the most widely used software (about 35%). The random effect (RE) probit is the most commonly used estimation method from our analysis. The reason for this is that most of the studies used binary choices, that is, forced choice alternatives are presented to respondents to make a choice from. However, we saw an increase in the use of advanced discrete choice modelling methods – mixed logit (MXL) and nested logit (NL).

Chapter 2 therefore gave an understanding into how the DCE was applied in various health and health related studies. It shows also which design method can be used and why. It helped to shape us in determining the choice of attributes, levels assigned, experimental design method and other areas.

Chapter 3 presented estimates of WTP for informal sector workers. From the literature reviewed in chapter 2, we realized that only one paper (Vroomen and Zweifel, 2011) looked at WTP for health insurance using a DCE method. Chapter 3 therefore looked at WTP for health insurance using a DCE from a developing country perspective. However, since the software method of generating experimental design dominated our review, and that the software SPSS was the second most widely used software, we therefore used SPSS to generate our experimental design. Eight informal sectors were used in this study, namely, petty trading, subsistence farming, commercial bike riding ("Okada"), cattle rearing, fishing, tailoring, mining and quarrying. WTP for an improvement in each of the attributes was estimated using a random effect logit method. Findings from the study showed that households mostly prefer two key attributes: the non-public provider and an improvement in moderate coverage.

Our study revealed that households were WTP more to have all attributes except the attribute waiting time wherein they were willing to accept compensation for it. Our findings suggested also that location – rural versus urban – matters in determining WTP. Rural and urban households were WTP 54591SLL ($12.41) and 87404SLL ($19.86) respectively. Our results showed that urban households were WTP more for health insurance than their rural counterparts. In addition, urban households were WTP 45066.9SLL ($10.24), which is about twice the amount rural households were WTP (24062.7SLL/$5.47) for having a non-public provider; and urban households were also WTP 36567.6SLL ($8.31) more than their rural counterparts (28500.1SLL/$6.48) for an improvement in coverage. The main reason for this is the level of awareness among urban households that is lacking among rural households, and as discussed in the literature, households are WTP more for health insurance when they are aware of the benefits they stand to gain. Our results also suggested that rural households were WTP about 249.1SLL ($0.06) less than their urban colleagues for a reduction in waiting time. Another key finding in this study was that the probability that a household will choose a contracted provider as against a public provider was higher for households in informal sector activities predominant in urban areas.

One of our findings in chapter 3 was that informal sector households prefer non-public to public provider systems. One of the reasons for this discussed in our study and in the literature was corruption in publicly provided health care systems. This caused us to look at the impact of corruption in a household's decision to participate in health insurance. In chapter 4 therefore, we investigated the impact of corruption on participation in health insurance using a mixed logit model.

Two measures of corruption within the health sector were looked at in this paper – household's perception of corruption within the health sector and free health care corruption (FHC), also known as actual corruption. We first looked at the relationship between the types of corruption and household characteristics. First we looked at the relationship between perceived corruption and household characteristics, our findings revealed that the relationship has opposite effects on households' perception of corruption in the health sector. For instance, a negative relationship existed between the informal sectors and those households that perceived corruption to be less while a positive relationship existed with those households that perceive the health sector to be very corrupt. The intuition for this is that households that strongly perceived corruption in the health sector are certain that corruption is prevalent either out of experience or based on happenings within the sector, whereas for those households who perceive corruption to be less are not certain whether corruption is prevalent. This explains the variation and change of signs. Irrespective of the sample you are looking at, participation in health insurance increases with coverage and non-public provider, but decreases with cost and waiting time. On the impact of corruption on participation, our study revealed that the probability of a household to participate in health insurance decreases with corruption. For rural households, FHC corruption impacts negatively while corruption perception impacts positively on participation in health insurance. For urban households, we saw the direct opposite. The implication of the impact of corruption on participation in health insurance is that corruption generates additional cost to households. WTP to participate is high for FHC corruption than corruption perception. Overall, FHC corruption impacts participation in health insurance more as households were WTP to participate more by about 43%.

In chapter 5, we looked at ability to pay (ATP) for health insurance, first by looking at perceived NEED and PART, and secondly, looked jointly at both perceived NEED and PART. We found out that households involved in informal activities predominant in urban areas, positively and significantly impact perceived NEED.

One key finding from our study was that perceived need for health insurance positively and significantly impacts participation in health insurance. Our finding also revealed that households do not have the ability to pay for health insurance. The result also shows that after accounting for the endogenous nature of perceived need for health insurance, its effect diminishes significantly. Failure therefore to account for the endogenous nature of need for health insurance led to an overestimation of the positive impact of perceived need on participation in health insurance.

Taking our analyses from chapters 2 to 5 into perspective, we provided a comprehensive picture of willingness and ability to pay for health insurance among informal sector workers in Sierra Leone using a DCE. We explored in detail issues overlooked in the literature – willingness and ability to pay for health insurance and the impact of corruption on participation in health insurance, especially in developing countries. Our findings suggested that informal sector workers are willing to pay for health insurance, but that they don't have the financial capacity to afford it. Bearing these points in mind, we now discuss some policy and research implications of these analyses.

6.3 POLICY AND RESEARCH IMPLICATIONS

We discuss below some of the policy and research implications from the findings of the analyses of the thesis. We looked at four specific areas of policy and research implications in this research: (1) a literature review of the application of DCE on WTP and health insurance; (2) WTP for health insurance; (3) impact of corruption on participation in health insurance; and (4) ATP for health insurance.

6.3.1 The application of DCE to WTP for Health Insurance: A Systematic Literature of the Literature

Our review revealed that the study of validity of the DCE methodology is limited in the literature. External validity is the least studied aspect of validity (3 studies), hence it is in its early stage of research. Studies are needed to explore this sensitive but crucial aspect in the literature.

6.3.2 Willingness to Pay for Health Insurance

Our study shows that households were WTP more for an improvement in coverage and having a non-public provider. In terms of location, we found out that households in urban areas were WTP more. The implications for policy for these findings are that policies should be directed towards improving the attributes coverage and non-public provider. Policy makers should increase their awareness raising on the need for households especially those in rural areas to join the scheme and the benefits they will get. This is important because it is clear from the literature that when households are aware of the benefit they'll accrue from joining such schemes, they can join.

In terms of methodology, it will be worth trying to see how the results will span if we use an efficient design and a large sample size by incorporating the other regions in the country. Apart from a forced choice used, we can also use opt – out option and a labelled design to see if households can behave the same way.

6.3.3 Impact of Corruption on Participation in Health Insurance

Our main finding here was that corruption increases the cost of participation in heath insurance scheme. The policy implication is that health care authorities should focus on health insurance schemes without corruption, since households are highly likely to participate in such schemes. Authorities should improve on policies to combat corruption in order to encourage more households to participate.

In terms of methodology, policy makers should focus on actual measures of corruption than corruption perception. Some other pilfering areas within the sector should be looked at. In most developing countries, policies are affected by regionalism, tribalism and allegiance to political parties, therefore as sensitive as corruption is, to incorporate the entire country will help in explaining the multidimensional facets of corruption.

6.3.4 Ability to Pay for Health Insurance

Our key finding in this paper was that households are willing to pay for health insurance, but do not have the financial capacity to pay for it. The policy implication is that health care authorities should focus on providing affordable health insurance schemes. A thoroughly planned and managed health insurance scheme will attract more households who will be willing to pay for it. In as much as the informal sector households are not able to pay for health insurance, one thing for certain is that a low cost and properly managed health insurance scheme will attract households in such sectors.

In terms of methodological issues, an instrumental variable method with good instruents should be used to do a joint estimation of perceived need and participation in health insurance. After which, the results can be compared again with the recursive bivariate probit model. In addition, there is need to increase the number of choice sets through the block system, say to 27, so that we can include many variables that were left out in the analysis.

6.4 CONTRIBUTIONS

Given the nature of the research carried out, this study adds to the existing body of literature in the field of health economics, more so in developing SSA countries. The contributions to knowledge made in this work are listed below:

- ✓ By developing a DCE as opposed to a contingent valuation approach, this study has enabled us to estimate WTP with respect to each of the attributes – improvement in coverage, having a public provider, having a non-public provider and a reduction in waiting time. This research has therefore an insight into the monetary values households attach to the attributes that make up the amount to pay for health insurance.

- ✓ The decision to investigate households' WTP for health insurance using a DCE generates awareness for the benefits associated with DCE study. Whilst almost all DCE studies have been developed outside SSA, this study provides a new insight into conducting DCE from an African country perspective.
- ✓ This study is the first to look at willingness and ability to pay for health insurance in Sierra Leone using the DCE methodology. The first study to use the DCE methodology
- ✓ One of few studies to review the application of DCEs to WTP for health outcomes including health insurance in health economics
- ✓ The first study to look at the impact of corruption on participation in health insurance. The study is also the first to use the DCE methodology to study the impact of corruption on participation in health insurance
- ✓ The first to look at the ability to pay for health insurance using an econometric approach.

6.5 SHORTCOMINGS OR LIMITATIONS OF THE RESEARCH

While the reasons discussed above are interesting findings with important policy and research implications, however, it is acknowledged that there are a number of limitations faced in this research.

First, a methodological limitation of the systematic review of the literature is it's over reliance on published sources, hence, limiting us from searching and using non-published articles. The implication of this is limiting the accurate representation of the state of DCE practice due to publication lags.

Second, the review focused only on published articles in English language. Studies done and published in other languages apart from English were left out in the review.

Third, the use of equal levels of attributes used in the DCE design in this study may impose a cost on the experiment because some attributes may naturally require more than three levels.

Fourth, the number of choice sets used limited the number of variables to use to just a maximum of 18. This was as a result of the point that the number of variables used should not exceed the number of choice sets.

6.6 CONCLUSION

Three major conclusions can be drawn from the thesis; firstly, that households are willing to pay for health insurance; secondly, that corruption increases the cost of health care and that actual corruption (FHC) impacts greatly on households participation in health insurance; and thirdly, informal sector households do not have the ability or financial capacity to pay for health insurance.

QUESTIONNAIRE

QUESTIONNAIRE FOR RESEARCH ON WILLINGNESS AND ABILITY TO PAY FOR HEALTH INSURANCE: A CASE STUDY OF INFORMAL SECTOR WORKERS IN SIERRA LEONE.

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INTRODUCTION

This questionnaire is designed to collect data for the purposes of analysing and estimating households' willingness and ability to pay for health insurance in Sierra Leone which, forms part of a PhD thesis. The project will also look at the impact of corruption on households' participation in health insurance respectively.

The questionnaire is divided into three sub-sections (A, B & C). Section A seeks to find out whether the household falls within the informal economic activities being targeted. Section B on the other hand presents the Discrete Choice Experiment (DCE) to respondents and section C deals with the socio-economic and demographic characteristics of the household.

You are being assured that all your answers will remain confidential. The answers will be published on a "no – name basis" and the results will form part of a PHD thesis and related papers.

Please remember this is a purely hypothetical exercise and will have no impact on your actual choice of health insurance/health care. The questionnaire will take approximately 40 - 45 minutes to complete

SECTION A

IDENTIFICATION OF INFORMAL ACTIVITY OF HOUSEHOLD

As head/representative of the household, please tick among the following informal sector activities your main economic activity/occupation

- Petty Trading
- Subsistence Farming
- Commercial Bike Riding (Okada)
- Cattle Rearing
- Fishing
- Tailoring
- Mining
- Quarrying

SECTION B

DISCRETE CHOICE EXPERIMENT

The following set of questions present you with 10 choices. Each of these questions asks you to state which Health Insurance Scheme (A or B) you prefer. However, Health Insurance Schemes A and B differs from each other based on the following:

- Type of Coverage provided by the schemes – this might be in the form of Simple, Moderate and Comprehensive coverage. Simple coverage refers to an outpatient treatment of minor diseases service; moderate coverage covers inpatient treatment of minor diseases together with performing minor operations services; and comprehensive coverage covers inpatient treatment of major diseases and performing major operations services.
- Waiting Time - Length of time you wait to see a medical officer and this may be 45 minutes; 60 minutes; and 90 minutes.
- Type of Provider - The type of hospital or health centre you visit for treatment and this may be a private, public or only contracted/non-public hospitals or health centres.
- Cost of the Health Insurance Scheme – this may be 4000SLL; 6000SLL; and 10000SLL. Also note that all the cost figures are monthly payments.

For Example:

Assuming a situation wherein the Government decides to set up a National Health Insurance Scheme. Imagine a situation in which you are to make a choice between Health Insurance **Schemes A or B**. Each of the schemes contains different decision making factors and a predetermined set of values. Please consider the following scenarios and select which Health Insurance Scheme you would prefer to choose.

Question	**Scheme A**	**Scheme B**
Coverage	Comprehensive	Moderate
Waiting Time (Minutes)	60	90
Choice of Provider	Private	Contracted
Cost (Sierra Leonean Leones – SLL)	6000	4500
Which Scheme would you prefer		
Are you willing to Participate in your chosen scheme? Yes or No.		

BLOCK A

Question 1	Scheme A	Scheme B
Coverage	Simple	Moderate
Waiting Time (Minutes)	45	60
Choice of Provider	Private	Public
Cost (Sierra Leonean Leones – SLL)	4000	6000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 2	Scheme A	Scheme B
Coverage	Comprehensive	Simple
Waiting Time (Minutes)	90	45
Choice of Provider	Contracted	Private
Cost (Sierra Leonean Leones – SLL)	6000	10000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 3	Scheme A	Scheme B
Coverage	Moderate	Comprehensive
Waiting Time (Minutes)	90	45
Choice of Provider	Private	Public
Cost (Sierra Leonean Leones – SLL)	10000	4000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 4	**Scheme A**	**Scheme B**
Coverage	Comprehensive	Simple
Waiting Time (Minutes)	45	90
Choice of Provider	Public	Contracted
Cost (Sierra Leonean Leones – SLL)	4000	6000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 5	**Scheme A**	**Scheme B**
Coverage	Moderate	Comprehensive
Waiting Time (Waiting Time)	60	90
Choice of Provider	Private	Public
Cost (Sierra Leonean Leones – SLL)	6000	10000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 6	**Scheme A**	**Scheme B**
Coverage	Comprehensive	Simple
Waiting Time (Waiting Time)	60	90
Choice of Provider	Contracted	Private
Cost (Sierra Leonean Leones – SLL)	10000	4000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 7	Scheme A	Scheme B
Coverage	Simple	Moderate
Waiting Time (Waiting Time)	90	45
Choice of Provider	Public	Contracted
Cost (Sierra Leonean Leones – SLL)	4000	6000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 8	Scheme A	Scheme B
Coverage	Comprehensive	Simple
Waiting Time (Waiting Time)	60	90
Choice of Provider	Private	Public
Cost (Sierra Leonean Leones – SLL)	6000	10000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 9	Scheme A	Scheme B
Coverage	Moderate	Comprehensive
Waiting Time (Waiting Time)	90	45
Choice of Provider	Contracted	Private
Cost (Sierra Leonean Leones – SLL)	10000	4000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

Question 10	**Scheme A**	**Scheme B**
Coverage	Simple	Comprehensive
Waiting Time (Waiting Time)	90	45
Choice of Provider	Public	Contracted
Cost (Sierra Leonean Leones – SLL)	10000	4000
Which Scheme would you Prefer		
Will you Participate in your Chosen Scheme? Yes / No.		

SECTION C

SOCIO-ECONOMIC CHARACTERISTICS OF HOUSEHOLDS

1. Region

Northern Province	Western Area

2. District

Bombali	Kambia	Koinadugu	Tonkolili
Port Loko	W/A Urban	W/A Rural	

3. Chiefdom

4. Town/Village

5. Location. Urban / Rural

6. How many Members do you have in your Household – those who Eat from the same Source

7. Household Rooster – List your Households' information as given below including you.

Name	Sex	Age	Relationship to household head	Marital Status	Educational Level

8. As Head of the Household, which one pertains to your Level of Education

No School	Primary	Adult	Basic	Secondary

9. Apart from your main economic activity listed above, what is your second major source of income?

10.Do you have any relative or friend in any other place outside the location of the household? Yes ☐ No ☐

11. If yes, how many? If No, move to question 14.

12. Do you normally receive money from him/her? Yes ☐ No ☐

13. If yes, please complete the table below:

Migrant(s)	Country/Town of Residence	How much received	How often

14. How many meals including breakfast are taken per day in your household?

15. How much does the household spend on food per month?

16. How much did the household spent in the last 30 days?

17. Can you please provide your main sources of expenditure in order of percentage/importance?

Feeding	Payment of School Fees	Health Care Expenditure	Others

18. From (17), we will be very grateful if you could please provide an estimate of your Monthly Expenditure as a household.

19. What is you/your households' main source of treatment when you are sick?

Self Treatment	☐	Traditional	☐	Health Centre	☐
Hospital	☐	Drug Peddlers	☐	Pharmacy	☐
None	☐				

20. Did you or any member of your household visited the Hospital/Health Centre in the last six months? Please complete the information below. Please list all visits of all members.

Name of Member	Visit to hospital/health centre in last six months Yes = 1, No = 0)	Have you been sick of Malaria or Typhoid fever in the last six months Yes/No

21. How far is your house to the nearest service below?

A Health centre/clinic you can go to?

B Hospital you can go to?

22. Do you have a household member who is between age 0 – 5 years; pregnant or a lactating mother? Yes / No

23. If Yes in (22) above, do they pay for Medicines or Services at the Hospital/Health Centre/Clinic? Yes / No

24. If Yes in (23) above, please tick one reason why you pay for such services?

Unaware it was Free	Medical Personnel asked for payment before treatment	Aware not to pay, but just gave a tip	Any Other Reason

25. How do you Perceive Corruption in the Health Hector?

Highly Corrupt	Corrupt	Less Corrupt	Not Corrupt

26. Have you ever had a situation where in your main economic activity was threatened by a shock? Yes / No

27. If yes, which shock?

28. Do you or any other member of your household SMOKES CIGARETTE / DRINKS ALCOHOL? Yes / No

29. Do you listen to news on the radio or read a newspaper? Yes No

30. We would be grateful if you could please provide an estimate of your household's monthly income? Please tick.

Less than 200,000SLL	200000SLL – 350000SLL	350000SLL – 500000SLL	500000SLL – 750000SLL	Above 750000SLL

As a guide from above, can you now please state your exact monthly income?

THANK YOU VERY MUCH FOR YOUR TIME AND EFFORT TO TAKE PART IN THIS SURVEY.