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Effects of Community-based Health Insurance on Child Health Outcomes and Utilisation of Preventive Health Services:

Evidence from Rural South-Western Uganda

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DEDICATION

To my late parents, Eriya Nsengiyunva Byarugaba Nshakira and Robinah Byarugaba
And
Prof Enoch Kwizera Nshakira

May you continue resting in eternal peace.

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Abbreviations

2SRI	Two Stage Residual Inclusion
ANC	Antenatal Care
ATE	Average Treatment Effect
ATET	Average Treatment Effect on the Treated
CBHI	Community-Based Health Insurance
CHMI	Centre for Health Markets and Innovations
CI	Confidence Intervals
DHS	Demographic and Health Survey
HDDS	Household Diet Diversity Score
HIV/AIDS	Human Immunodeficiency Virus/ Acquired Immune Deficiency Syndrome
IPW	Inverse Probability Weighting
IRR	Incidence Rate Ratios
ISSA	International Social Security Association
IV	Instrumental Variables
LLIN	Long Lasting Insecticide Treated Mosquito Nets
MAR	Missing at Random
MNAR	Missing Not at Random
MOH	Ministry of Health (Uganda)
MUSPH	Makerere University School of Public Health
OLS	Ordinary Least Squares
OR	Odds Ratios
PCA	Principal Components Analysis
PCV	Pneumococcal Conjugate Vaccine
SD	Standard Deviation
SE	Standard Error
TBA	Traditional Birth Attendants
TSLS	Two Stage Least Squares
UBOS	Uganda Bureau of Statistics
UCBHFA	Uganda Community-based Health Financing Association
UGX	Uganda Shillings
UNCST	Uganda National Council of Science and Technology
USAID	United States Agency for International Development

USD	United States Dollar
VHT	Village Health Team
VIF	Variance Information Factor
WHO	World Health Organisation
ZINB	Zero-Inflated Negative Binomial model

Abstract

With a new focus on health for all through universal health coverage, Community-Based Health Insurance (CBHI) has been proposed both as a building block for health systems financing and providing financial protection from catastrophic expenditures. Research on these two broad purposes for CBHI has been immense over the last couple of years. However, one area that remains under-researched is whether it has any effects beyond these two and in particular on child health outcomes or preventive health practices. The absence of research in this dimension is often attributed to the difficulty of disentangling endogeneity between health insurance and health outcomes. Research presented in this thesis aims at responding to this research gap by studying the impact of CBHI on child stunting and on preventive health practices, using a case study from south-western Uganda. The study posits three basic questions: (1) what determines enrolment in and continued participation in CBHI in rural south-western Uganda? (2) Does CBHI contribute to the reduction of stunting? And (3) can CBHI nudge households in utilisation of preventive health strategies and treatments?

To respond to these questions, a household survey covering 464 households was conducted in Kabale and Rukungiri districts, particularly in regions that are primarily serviced by Kisiizi Hospital CBHI scheme. From this data, three analytical chapters responding to three questions are developed. The first chapter (appearing as Chapter Two in the thesis) uses logistic regression methods to understand the drivers of enrolment and continued participation in insurance. The study finds significant positive correlations with household socioeconomic status, knowledge about insurance, the number of burial groups in the village that participate in CBHI as well as the size of the burial group a household belonged to. Chapters three and four delve further into causal analysis and respectively utilise novel Two-Stage Residual Inclusion Instrumental Variables and Inverse Probability Weighting estimations. Inverse Probability Weighting facilitates estimation of causal effects after controlling for observable determinants of CBHI uptake while the Instrumental Variable method helps model a combined effect of selection into CBHI and CBHI intensity measured by the number of years a household had participated.

Results indicate that an extra year in CBHI was associated with reducing the probability of child stunting by 5.7 percentage points. This implied that for a child's under-five life span, the probability of stunting could be reduced by 28.5 percentage points due to a household's enrolment in CBHI. In addition the poorest households had a higher rate of reducing the probability of child stunting indicating that CBHI was effective in improving health outcomes of the poorest. In Chapter Four, focus is on seven preventive health strategies and treatments available in rural Uganda. These were water treatment, child deworming, vitamin A supplementation, iron supplementation and use of long lasting insecticide treated mosquito nets, handwashing and receiving the new vaccine for child pneumonia, Pneumococcal Conjugate Vaccine (PCV). Utilising inverse probability weighting of the propensity score, significant average treatment effects are found in four of the seven outcomes measured, namely, using a long lasting insecticide treated mosquito

nets, water treatment, iron supplementation and deworming. Moreover, significant average treatment effects on the treated are found on five of the seven outcomes, including receiving PCV. By and large, this research adds to the thin layer on CBHI effects on health outcomes and utilisation of preventive health interventions.

Zusammenfassung

Mit dem neuen Fokus auf „Gesundheit für alle“ durch universelle Gesundheitsvorsorge wurden community-basierte Krankenversicherungen (CBHI) einerseits vorgeschlagen als ein Baustein für die Finanzierung von Gesundheitssystemen und andererseits für die Schaffung finanzieller Absicherung gegen katastrophalen Gesundheitsausgaben. In den letzten Jahren wurde intensive Forschung zu diesen beiden Aspketen von CBHI betrieben. Allerdings bleiben Forschungslücken bezüglich weitergehender Effekte, besonders auf Gesundheitsoutcomes bei Kindern oder auf präventive Gesundheitspraktiken. Die wenige Forschung in dem Bereich wird oft begründet mit der Endogenität und den damit einhergehenden Schwierigkeiten bei der Analyse von Krankenversicherungen und Gesundheitsoutcomes. Diese Arbeit adressiert die Forschungslücke bezüglich CBHI und deren Effekt auf Stunting bei Kindern und präventive Gesundheitspraktiken in Form einer Fallstudie in Südwestuganda. Drei grundsätzliche Fragen werden gestellt: (1) Was bestimmt die Entscheidung für und langfristige Teilnahme an CBHI-Programmen im ländlichen Südwesten Ugandas? (2) Trägt CBHI zur Reduzierung von Stunting bei? (3) Vermag CBHI die Haushalte in Richtung präventiver Gesundheitsstrategien und -behandlungen zu „nudgen“?

Um diese Fragen zu beantworten, wurden Befragungen in 464 Haushalten in den Distrikten Kabale und Rukungri durchgeführt. In diesen Regionen wird hauptsächlich das Kisiizi CBHI-Modell genutzt. Die Daten werden in drei analytischen Kapiteln zur Beantwortung der Forschungsfragen ausgewertet. Das erste Kapitel (erscheint als Kapitel 2 in der These) nutzt Methoden der logistischen Regression, um die Antriebskräfte für die Entscheidung für und langfristige Teilnahme an Versicherungen zu verstehen. Die Studie findet signifikante positive Zusammenhänge mit dem sozioökonomischen Status des Haushalts, dem Wissen über Versicherungen, der Anzahl an Bestattungsgruppen in den CBHI-Dörfern sowie der Größe der Bestattungsgruppe des jeweiligen Haushalts. Kapitel 3 und 4 vertiefen die kausale Analyse und nutzen neuartige Two-Stage Residual Inclusion Instrumentvariablen bzw. Inverse Probability Weighting Schätzungen. Inverse Probability Weighting ermöglicht die Schätzung kausaler Effekte, wenn für beobachtbare Determinanten des Eintritts in community-basierte Krankenversicherungen kontrolliert wird. Die Instrumentvariablen-Methode hilft bei der Modellierung des kombinierten Effekts von CBHI-Aufnahme und CBHI-Intensität gemessen an der Dauer der Teilnahme des Haushalts.

Die Ergebnisse zeigen, dass ein zusätzliches Jahr mit CBHI mit einem Rückgang von Kinder-Stunting um 5,7 Prozentpunkte verbunden war. Dies impliziert, dass im Falle einer Teilnahme des Haushalts an CBHI die Wahrscheinlichkeit für ein Kind in den ersten fünf Lebensjahren von Stunting betroffen zu sein um 28,5 Prozentpunkte reduziert werden konnte. Zusätzlich zeigten die ärmsten Haushalte einen höheren Rückgang in der Wahrscheinlichkeit von Stunting bei Kindern. Dies lässt darauf schließen, dass CBHI einen positiven Effekt auf die Gesundheitsoutcomes der Ärmsten hatten. Der Fokus in Kapitel 4 liegt auf sieben präventiven Gesundheitsstrategien und -behandlungen im ländlichen Uganda. Diese sind die

Aufbereitung von Trinkwasser, Entwurmung von Kindern, Vitamin A- sowie Eisenergänzungsmittel, mit Insektenmittel behandelte Moskitonetze, Händewaschen und die Impfung von Kindern mit dem neuen Pneumokokken-Konjugatimpfstoff (PCV) gegen Lungenentzündung. Signifikante durchschnittliche Behandlungseffekte (Average Treatment Effect) konnten durch den Gebrauch von Inverse Probability Weighting des Propensity Scores bei vier der sieben Maßnahmen gemessen werden, nämlich bei Moskitonetzen, Wasseraufbereitung, Eisenergänzungsmitteln und Entwurmung. Außerdem wurden bei fünf der sieben präventiven Maßnahmen signifikante durchschnittliche Behandlungseffekte auf die Behandelten (Average Treatment Effects on the Treated) gefunden, einschließlich bei PCV Impfung. Diese Studie trägt zur Erforschung der Effekte von CBHI auf Gesundheitsoutcomes und den Gebrauch präventiver Gesundheitsmaßnahmen bei.

CHAPTER

ONE

INTRODUCTION

1.1 Introduction

Health shocks are a constant occurrence in households across developing countries (Dercon et al., 2004) and lead to millions of people falling into poverty (Xu et al., 2003, 2007) in the absence of formal insurance mechanisms. One of the ways in which rural households mitigate the effects of catastrophic shocks is by drawing on informal insurance networks, borrowing and asset depletion (Dercon, 2002; Leive and Xu, 2008; Yilma et al., 2014). However, informal insurance mechanisms are often insufficient to provide full protection to households in distress (Goldstein et al., 2004; Morduch, 1999). Poor rural households therefore face multiple burdens of higher illness incidence, low access to services and insufficient means of financing health care in times of health shocks.

Over the last couple of decades, Community-based Health Insurance (henceforth CBHI) has evolved as one of the solutions for preventing rural households from deprivation through asset protection (Parmar et al., 2012), facilitating equitable access to care (Ranson et al., 2007) and providing extra resources for health systems financing (Carrin et al., 2005). The last couple of years have therefore witnessed tremendous research on CBHI to understand how much these objectives are achieved. However, certain aspects of CBHI are still under-researched, in particular in relation to health outcomes and preventive health. Research presented in this thesis aims at providing some evidence in this regard. Precisely, the research uses a case study of a relatively large CBHI scheme in rural south-western Uganda and explores effects of membership in CBHI on child stunting and preventive health practices. In addition, for Uganda, less is known about the determinants of enrolment into CBHI schemes. This research provides some pioneering quantitative evidence on the determinants of enrolment.

1.1.1 What is community-based health insurance?

Community-based health insurance (CBHI), is one of the several platforms of risk sharing for health eventualities among the informal sector population in developing countries. It is often referred to as voluntary health insurance or mutual health insurance and often operates under the ethics of mutual assistance, solidarity and collective risk pooling of health risks (Atim, 1998; Wang and Pielemeier, 2012). In their earlier exploratory study, Bennett et al. (1998) found that kinship and trust were essential components of CBHI schemes, with schemes characterised by social homogeneity and imbedded trust between members. However, Bennett et al. (1998)also reveal a diversity in the landscape of CBHI schemes often based on the degree of social cohesion and levels of demand for insurance and community engagement in administration and management. Having been highly supported by the World Health Organisation (WHO) as a pathway for universal health coverage (WHO, 2005, 2010), a recent WHO report (Mathauer et al., 2017) expounds that the diversity within CBHI schemes depends on how much the central features are practiced. These include, but may not be limited to:

- Communities are involved in setting up and managing the scheme;

- Prepayment mechanisms for pooling health risks are conducted at the community level or group level where the participants share occupational or geographical characteristics;
- Premiums are often flat-rate, set by the community and independent of individual risks;
- Entitlement to benefits is limited to making contributions to the group;
- Affiliation is voluntary and[1], and;
- Scheme operate on a non-profit basis

1.1.2 The evolution of community-based health insurance

The evolution of community-based health insurance has experienced two major watershed moments. The first one is the 1978 Alma Ata declaration on Primary Health Care (WHO, 1978), a pivotal point in health systems in developing countries. Among the recommendations, the conference made was to "encourage and prioritise various ways of financing primary health care, including, where appropriate, such means as social insurance, cooperatives and all available resources at local level through the active involvement and participation of communities" (WHO, 1978, p. 30). The second moment, more focused on African countries, was the 1987 Bamako Initiative in which African Ministers of Health agreed in a framework that recognised that communities were essential to the financing primary health care (UNICEF, 1989, p. 50). The recommendation of the Bamako initiative were crucial given the 1980s economic recession in most African countries. Two pilot projects tested the viability of establishing community revolving funds for purchase of medicines (Kanji, 1989; Lancet Editorial, 1988). These moments created the foundation for the formation of non-state health insurance programmes across several African countries such as the Bamwanda scheme in Democratic Republic of Congo(Criel and Kegels, 1997), Murewa scheme in Zimbabwe (Criel et al., 1996) and several across East Africa in the 1980s and 1990s (Musau, 1999).

The evolution of community-based health insurance benefited from significant financial and policy input from international organisations. The Alma-Ata and Bamako recommendations were supported by UNICEF and the World Health Organisation and UNICEF dedicated 180 million United States dollars for initial investments in drug revolving funds as precursors to insurance schemes (Garner, 1989; Kanji, 1989). The new schemes in East and West Africa received financial and technical support from donors (Diop et al., 2006; Musau, 1999). The influential World Health Reports further elevated the importance of CBHI. On the overall financing of health systems, the World Health Report 2000 suggested that "in low income countries, where there are usually high levels of out-of-pocket expenditure on health and where organizational and institutional capacity are too weak to make it viable

[1]While voluntary participation is one of the main traits, not all programmes have voluntary participation. For instance, community-based health insurance in Rwanda is mandatory for all citizens without any other insurance according to a law passed in 2015 (Nyman, 2008)

to rely mainly on general taxation to finance health, this (financing health systems) means promoting job-based contribution systems where possible, and facilitating the creation of community or provider-based prepayment schemes" (WHO, 2000, p.98). The World Health Report 2010 positioned CBHI as an integral component of achieving universal health coverage and stated that "community health insurance, or micro-insurance, can also be an institutional stepping stone to bigger regional schemes, which in turn, can be consolidated into national risk pools" (WHO, 2000, p.98), a position that has been supported by researchers as well (Bennett et al., 2010; Wang et al., 2012).

From this background, social insurance and voluntary insurance schemes, including CBHIs, have evolved across developing countries with the main purpose of reaching out to the poor (Van Der Gaag, 2009). In earlier studies on existing schemes, Bennett et al. (1998) recorded 81 programmes as of 1997 and Ekman (2004)'s systematic review included studies covering 178 schemes. The Centre for Health Markets and Innovations (CHMI) which collects basic information on such schemes had, as of November 2017, recorded 200 health micro-insurance schemes operating in low and middle-income countries specifically targeting poor households[2]. The expansion of CBHI (plus social insurance and other micro-health insurance) attests to the realisation that CBHI is increasingly becoming integral in financing health systems across developing countries (Carapinha et al., 2011; Carrin et al., 2005; Lagomarsino et al., 2012).

Research on CBHI has also grown exponentially, as shown in Table 1, indicating recent systematic reviews of literature on the topic. But as research grows, therein lies our main problem to which this thesis will try to address, in that this literature concentrates on enrolment and dropout, financial protection and payment systems, quality of care and health services utilisation. The research that addresses possible effects of insurance on health improvements and behaviour change in use of preventive care is very thin. Of the reviews assessed (Table 1), only one, Acharya et al. (2013) discuss health outcomes. Of the 19 studies included in Acharya et al. (2013), only six discussed health outcomes, something which the reviewers also found "surprising". Though the reviewers consider that financial protection is always the main objective of health insurance, they also suggest that if a range of health outcomes such as reduced mortality change due to insurance uptake, such a change would be attributed to the effect of insurance. This, therefore, forms the foundation of the problem this thesis tries to address in investigating the possible health outcome and preventive health behaviour change associated with CBHI uptake in Uganda.

[2]Data was accessed on 20th October 2017. While this database is, to the best of our knowledge, the most comprehensive collection on micro-insurance programmes in developing countries, it is less than conclusive as it misses out some famous programs we would expect to be recoded such as Nouna Scheme in Burkina Faso so we believe the number of existing programmes is much higher than what is currently registered.

Table 1.1: Synthesis of systematic reviews on CBHI (2004-2016)

	Enrolment, dropout willingness to pay	Financial protection resource mobilisation	Quality of care	Utilization of health services	Health Outcomes	
Spaan et al (2012)		x	x	x		159 studies
Mebratie et al (2013)	x	x		x		46 studies
Adebayo et al (2015)	x					25 studies/ 27 countries
Dror et al (2016)	x					54 studies / 56 countries
Ekman (2004)		x	x			36 studies /178 schemes
Robyn et al (2013)		x				34 studies / 32 schemes
Acharya et al (2013)	x	x		x	x	19 studies / 11 countries
Comfort et al (2013)				x		29 studies
Nosratnejad et al (2016)	x					16 studies/ 10 countries
Fadlallah et al (2018)	x					51 studies

Source: Author's depiction from the cited literature

1.2 The problem statement

While there has been tremendous growth in CBHI-related research very few studies focus on health outcomes as direct effects of health insurance. For most developing countries, the understanding of health insurance impacts on health outcomes can be impeded by two main issues, namely; endogeneity of health insurance and health outcomes, which presents challenges in estimating the effects, and availability of data.

The first issue is a methodological, one regarding endogeneity of health insurance and health outcomes (Levy and Meltzer, 2008). Endogeneity, in this case, implies that an individual's or household health insurance status is most likely related to his or her health status. For instance, healthier people are most likely to possess more income or income generating capacity from which they are able to pay for insurance premiums. Richer people with better health are more likely to not join health insurance arrangements since they do not face profound financial barriers from accessing health care. Richer people are also more likely to have more and better education and information to facilitate their choices for both healthcare and health insurance decisions. This would imply self-selection of certain groups of the population hence adverse selection. Conversely, people with a higher likelihood of getting sick are more likely to purchase insurance as a precautionary measure for income protection while those with a less likelihood of falling ill do not purchase insurance since payment of the premiums without using insurance would be seen as an income loss to them. This would lead to moral hazard. These concepts of moral hazard and adverse selection have been well articulated in broader health insurance literature (Cutler and Zeckhauser, 1998, 2000; Pauly, 1974) and in particular voluntary health insurance programmes in developing countries (Parmar et al., 2012; Wang et al., 2006; Zhang and Wang, 2008). Due to these sources of endogeneity, it is very difficult to disentangle the mechanisms through which health insurance affects health outcomes in the absence of panel data or experimental data.

The second challenge is the availability of data on insurance. In most developing countries, insurance penetration, including health insurance, is very low, often below 1 percent. In rural areas, it would be almost non-existent. This problem is not only limited to CBHI but all other types of health insurance as well, especially when there are no government-led social health insurance programmes. Because of these two reasons, much is not known about the effect of health insurance on health outcomes. This study focuses on Uganda, a country with relatively long experience in CBHI implementation but with very limited evidence of its health improving impacts. Generally, there are two main issues of concern and interest with CBHI in Uganda. First, while there have been some studies that try to understand enrolment patterns (Basaza et al., 2007, 2008; Twikirize and O'Brien, 2012), these studies are qualitative and to the best of our knowledge no quantitative study has been undertaken in understanding the reasons why households or individuals enrol or refuse to enrol in CBHI has been undertaken. This lack of quantitative studies is further exacerbated by lack of data to undertake the analysis simply because of low insurance penetration. Secondly, as mentioned earlier, the existing studies do not look into effects on health outcomes, whether of curative or preventive nature.

1.3 Research objectives

Research in this thesis, therefore, has three main objectives. The first objective is to quantitatively understand the determinants of enrolment in insurance in rural Uganda. The second objective is to ascertain the possible CBHI impacts on child stunting as an indicator of long-term child health status. The third objective, related to the second is to investigate the effects of CBHI membership on uptake and utilisation of preventive health strategies. From these objectives, therefore, this study aims to respond to three main research questions.

1. What are the determinants of enrolment in community-based health insurance in rural Uganda?
2. Does community-based health insurance lead to a reduction in stunting among rural Ugandan under-five children?
3. Can health insurance nudge behaviour change towards the improved use of preventive health practices in households with under-five children?

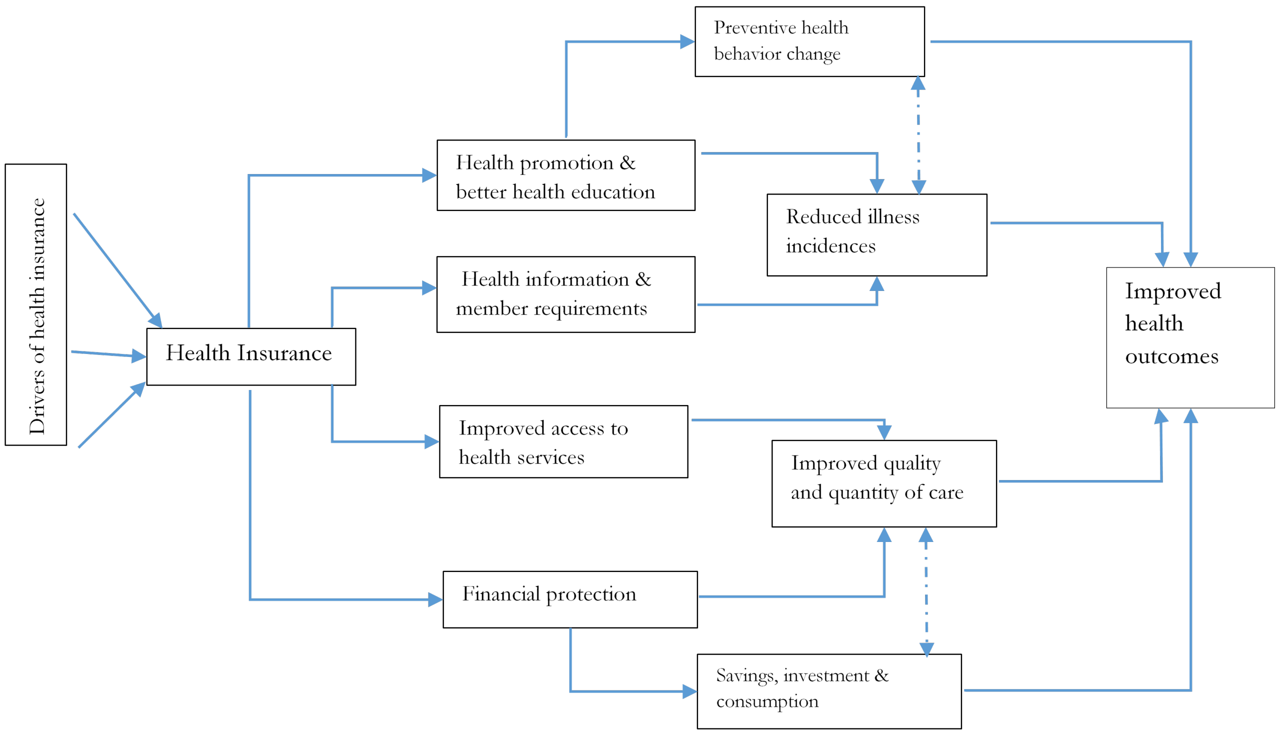
This research will contribute to the literature on health insurance impacts on health outcomes in developing countries especially in poorer rural areas that suffer large deficiencies and inequities in health outcomes. Moreover, for Uganda, the outcomes of this research will be relevant to policy formulation for the national health insurance scheme, most importantly learning from domestically available examples.

1.4 Conceptual framework: pathways from health insurance to improved health outcomes

This simple conceptual framework shown in Figure 1 elucidates on the pathways through which health insurance influences health outcomes. The decisions to enrol in health insurance are often determined by several drivers such as government policy, education, income and individual capabilities to pay required insurance subscriptions or community social network effects. Some of the determinants are macro-level policy changes like the case of state-level insurance programs such as found in Rwanda, Ghana, Vietnam, and China. Others are micro-level household decision-making mechanisms where new health insurance instruments have been introduced. Yet others are largely community-based determinants such as social networks and access to alternative health services, which somehow induce decision making.

Health insurance then leads to health promotion and better health education especially with state-led social insurance systems in developed and middle-income countries (ISSA, 2007). In developing countries, social capital, which is crucial for enrolment in health insurance (Fenenga et al., 2015; Mladovsky, 2014) can be leveraged on for health promotion and health education (Coe and Beyer, 2014; Eriksson, 2011; Hawe and Shiell, 2000; Kimball et al., 2013). In some instances, CBHI interventions are coupled with health promotion activities such as water treatment equipment and mosquito nets provided to members

Figure 1.1: Conceptual Framework of Health Insurance Linkages to Health Outcomes



Authors depiction

Health information plays a major role in insurance decisions. People with more information about their health are more likely to enrol or refuse to enrol in health insurance depending on the kind of information they have. Similarly, people with more information about health insurance itself are more likely to enrol as it is well established in the enrolment literature that more knowledge and information are important predictors of enrolment (Dror et al., 2016). The focus is not on these information effects but rather on the information benefits that accrue to health insurance enrolment. For instance, Panda et al. (2015) found that households with insurance had better knowledge of preventive health regarding water, air and vector-borne illnesses in India implying that household which enrolled in health insurance were also more likely to receive information about their general health either from insurance providers or from peers enrolled in CBHI. From the simple conceptual framework above, it is derived that the benefits accruing from health promotion and health information give households an edge to reduce illnesses and at the same time prevent them, thus improving their health outcomes.

As Table 1 shows, literature regarding the effect of insurance on financial protection and improved access to health services is indisputably vast. The conceptual framework shows that financial protection releases the would-be health expenditures to other uses such as savings, investments, and consumption and also provide extra resources for health system (Asfaw and von Braun, 2004a,b) which would, in turn, increase the quality and quantity of care received by the insured. For instance, insured people are more likely to seek care sooner, and spend more days in the hospital, compared to the uninsured. Through these mechanisms, insured people would realise improved health outcomes.

In the context of this thesis, health improvements are viewed in two main ways. The first one is child anthropometrics, a measure of both long term and short term health status for children. The second measure of health improvement is through preventive health. The interest here is in understanding how insurance influences the utilisation of both clinical preventive health products such as vitamin A and iron supplementations and home-based preventive health strategies such as water treatment and using of long-lasting insecticide mosquito nets.

1.5 Study area in the broader context

Uganda is located in East Africa, along latitude $4°12'$ and $1°29'$ and longitude $29°34'$ and $35°0'$ and a total land mass of 241,550 km^2 (UBOS, 2016). The country's population is estimated between 37.7 million (UBOS, 2017) and 41.3 million people (World Bank, 2017). A recent survey suggests that 27 percent of the population were living below the national poverty line in 2016 (UBOS, 2017) having increased from 19.5 percent in 2012 (UBOS, 2014a). In terms of the international poverty line, 34.6 percent live below US$1.9 a day in 2011 prices while close to 65 percent live below US$3.1 a day (World Bank, 2017). About 83.6 percent reside in rural areas and 72 percent are employed in agriculture (World Bank, 2017).

1.5.1 Health and development in Uganda

Uganda's health sector operations are guided by 10-year national health policies and 5-year health sector development plans[3]. In terms of infrastructure, the last decade has seen a growth in the number of health facilities from 3,443 health facilities in 2004 to 5,229 health facilities in 2012, 54 percent of which were public health facilities (UBOS, 2016). Table 2 below provides more statistics on the status on several health indicators. As of 2015, life expectancy was 59.5 years and maternal mortality rate had reduced from 100 children per 1,000 live births in 2006 to 55 children. However, the annual population growth rate remains one of the highest in the world at 3.3 percent. On average, women in the reproductive age bracket have close to six births in their reproductive lifetime (World Bank, 2017).

One of the four strategic agendas of the current 2015/16 - 2019/20 development plan is to reduce financial risk through establishing a national health insurance

[3]Currently, the national health policy is from 2010 to 2020(MOH, 2015)and the health sector development plan is from 2015 to 2020 (MOH, 2015)

Table 1.2: Selected health indicators in Uganda

Health indicator	2006	2011	2015
Annual population growth rate	3.5	3.4	3.3
Life expectancy at birth, total (years)	53.6	57.7	59.5
Maternal mortality ratio (modeled estimate, per 100,000 live births)	481	408	343
Mortality rate, under-5 (per 1,000 live births)	99.7	69.8	54.6
Anti-retroviral therapy coverage (% of people living with HIV)	8	24	67****
Community health workers (per 1,000 people)	0.194*		
Exclusive breastfeeding (% of children under 6 months)	60.1	63.2	65.5[1]
Immunization, DPT (% of children ages 12-23 months)	64	82	78
Immunization, measles (% of children ages 12-23 months)	75	75	82
Improved sanitation facilities (% of population with access)	17	18.3	19.1
Improved water source (% of population with access)	66.1	74.2	79
Low-birthweight babies (% of births)	14 1	1.8	
Physicians (per 1,000 people)	0.12*	0.117**	
Pregnant women receiving prenatal care (%)	93.5	93.3	95.4
Prevalence of HIV, total (% of population ages 15-49)	7.8	7.3	6.5****
Prevalence of stunting, height for age (% of children under 5)	38.7	33.7	29[1]
Prevalence of underweight, weight for age (% of children under 5)	16.4	14.1	11[1]
Prevalence of wasting, weight for height (% of children under 5)	6.3	4.8	4[1]
Use of insecticide-treated bed nets (% of under-5 population)	9.7	42.8	74.3
Vitamin A supplementation coverage rate (% of children ages 6-59 months)	71	60	66***

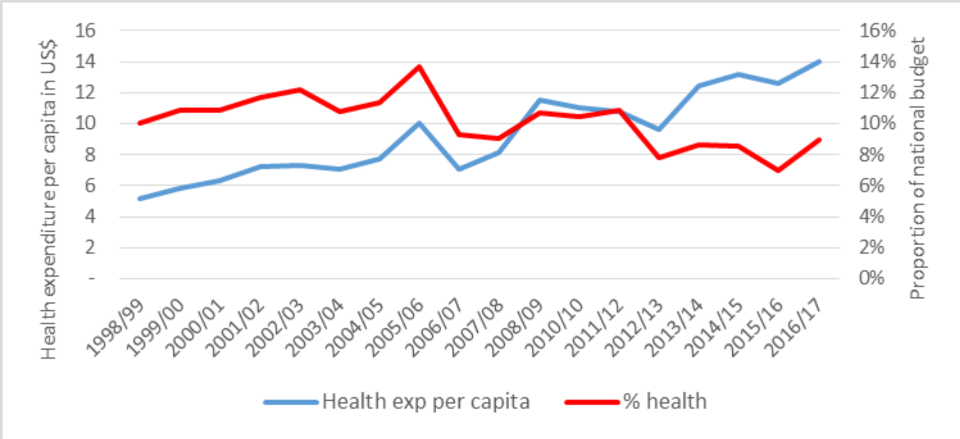
Data from World Development Indicators (WDI) 2017, accessed in October 2017.
Years of recorded indicated for * 2005, **2010, ***2014 & ****2016 respectively.
[1] Data from Demographic and Health Survey 2016

programme (MOH, 2015). Currently, there is no state-supported health insurance program and private health insurance is very small, covering about 5 percent of the population. However, a recent national survey indicates a willingness to purchase health insurance of higher than 40 percent (UBOS, 2017). Health services, by and large, are officially financed by taxes through direct budgetary allocations. Budget allocations for health services, however, remain low, especially in tandem with population growth rate and unofficial payments in the health sector remain rampant (Hunt, 2010). A review of the national budgets indicates that health budgets as a proportion of national budget has declined consistently since 2005. The government spends just about US$14 for every citizen.

1.5.2 Health sector governance under decentralisation

In line with the Decentralisation Act of 1997, health services, like other public services are decentralised. Uganda's health care delivery system is organised in a decentralised manner such that certain health services are offered at specified levels of government administration. Districts are the highest level of sub-national administration and local governments have a responsibility to provide, manage and maintain health services and other public services (Muriisa, 2008). National and regional referral services are directly accountable to the central government while general hospitals and health centres are accountable to the district local governments. Local governments receive about 52 percent of all health sector budgets but

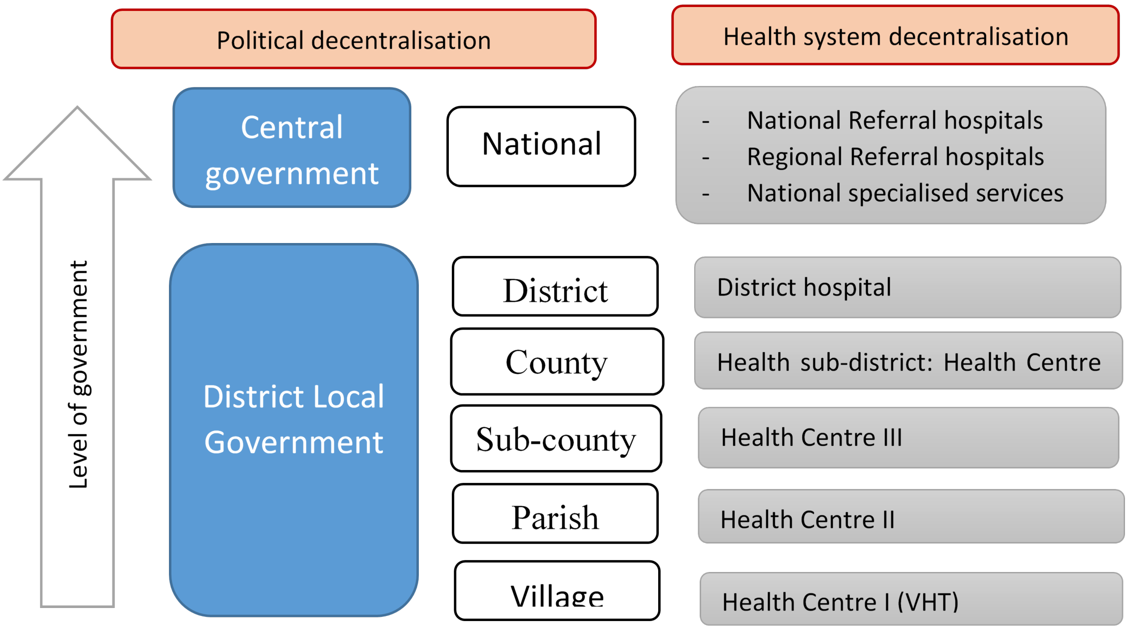
Figure 1.2: Government health expenditure 1998/1999 - 2016/2017



Source: Budget data from approved estimates of expenditures 1998/1999 to 2016/17 US$ conversion rates and population data used fromWorld Bank (2017)

funds are insufficient in relation to the health needs. In addition, districts are not able to supplement central government resources with additional locally generated resources because of inability to locally mobilise extra resources. 98 percent of all local government budgets are resources from the central government (World Bank, 2013).

Figure 1.3: Health sector decentralisation



Source:Author's depiction based on MOH (2000)

The experience of decentralisation in health services has been mixed. On the one hand, communities exercise more participatory powers with significant input into local planning. They have, however, limited autonomy on financial planning and resource allocation and are not able to allocate resources to local (health) needs (Akin et al., 2005; Alonso-Garbayo et al., 2017). The inability to either re-allocate resources or supplement budgets with local revenues has weakened the quality of decentralisation (World Bank, 2014). For instance, a 2009 study established that only less than 40 percent of Health Centre IVs were fully functional and only 33 percent of general hospitals were properly equipped. Furthermore, only one-quarter of all the districts had fully functioning community health workers and newly created districts did not have the necessary infrastructures (World Bank, 2009). In addition, over 40 percent of approved health sector positions in districts were vacant in 2014 (MOH, 2015) and the distribution of health infrastructure was highly uneven in that, about one-third of the districts did not have a general hospital (MOH, 2014).

As the number of districts has increased rapidly from 45 in 1997 to 112 in 2012 (World Bank, 2014)[4], questions remain over the efficacy of new districts and the effectiveness of existing ones. A recent service delivery report found that health (and education) workers were significantly ill-equipped to provide the required services. Tsimpo et al. (2017) find that only 27 percent of clinical health workers could correctly diagnose five illnesses and rural areas were even more disadvantaged with only 17.5 percent able to carry out the correct diagnosis. Moreover, the authors found that almost 52 percent of the health workers were regularly absent from duty.

While the health system suffers from multiple deficiencies one of the main challenges is inadequate financing. A multiplicity of deficiencies can be reduced with increased finances into the sector. The proposed National Health Insurance Bill will pass a law that will require formal sector workers and their employers to contribute 8 percent of their income to the national health insurance scheme. However, it is not yet clear how resources will flow from the scheme to fund different aspects of the health sector.

1.5.3 Health financing in Uganda

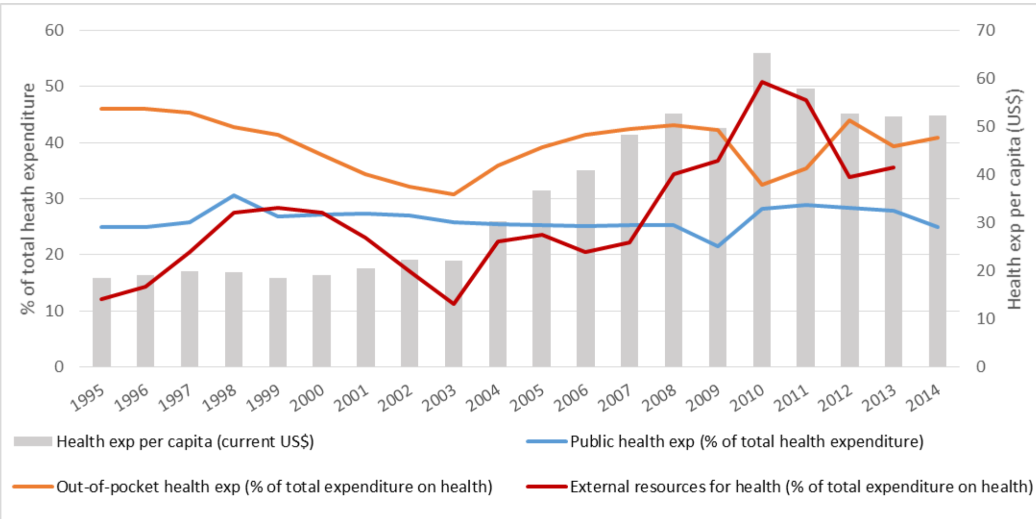
The current policy of financing health through taxes was adopted in 2001 (Burnham et al., 2004; Nabyonga Orem et al., 2005). Under this policy, public (government) health facilities do not charge user fees to access basic services while private not for profit health facilities charge user fees but also receive some government subsidies (Amone et al., 2005; Okwero et al., 2010). The reason for removing user fees was to increase access to services, especially the poor people which was partly achieved. Analysis undertaken a couple of years after policy change indicated that access to and utilisation of services for poor households improved (Nabyonga Orem et al., 2005; Xu et al., 2006).

However, despite the improvements in access to services, two issues remain of outstanding concern. The first one is that there was a very limited change in access

[4]In September 2015, the parliament created 23 more new districts to be created between July 2016 and July 2019, bringing the total number of districts to 135 by 2020. See http://www.parliament.go.ug/index.php/about-parliament/parliamentary-news/680-parliament-creates-23-new-districts

to specialised and other tertiary level services offered by hospitals by the poor. Instead, increase in services access happened only at lower level government health units that provide only primary health care (Nabyonga Orem et al., 2011). This possibly implies that services with the highest burden of user fees were still not accessible by the majority of the population though overall access to services improved for the rural poor people (Pariyo et al., 2009). The second outstanding issue was that there was no improvement in the incidence of catastrophic health payments by poor people (Xu et al., 2006). In 2006, 37 percent of the would-be health services users did not seek care due to financial difficulties while 28 percent of all households had catastrophic health payments (Okwero et al., 2010)[5]. The incidence of catastrophic health payments remains high (Kwesiga et al., 2015) and generally poor people remain disadvantaged in access to services (Kiwanuka et al., 2008). By and large, the Ugandan health financing policy has been summarized as a paradox of increasing required accessibility to primary health care services but increasing the financial burden to households (Nabyonga Orem et al., 2011).

Figure 1.4: Proporion of total health expenditure by source



Source: World Development Indicators(World Bank, 2017)[6]

As Figure 4 above indicates, the health sector is increasingly reliant on resources from other sources other than the government's financing, as the case should be. The main message in the graph is that while per capita health expenditure has increased over time, the government's contribution to total health expenditure has not improved, remaining below 30 percent in all the years between 1995 and 2014. Instead, the health sector is increasingly dependent on external resources for health (foreign aid) and most importantly households, through out-of-pocket expenditures. Out of pocket expenditure remains the most prominent source of health financing in the country, accounting for 41 percent of total health expenditure in 2014. A dependency on out of pocket expenditure has been related to unofficial payments (bribes) in the health sector (Hunt, 2010; Hunt and Laszlo, 2012).

[5]The measure for catastrophic health payments used was households spending on health equivalent to 10 percent or more of total household income.

1.5.3.1 The landscape of health insurance in Uganda

One way to mitigate health-related impoverishment (Kwesiga et al., 2015; Meessen et al., 2003) is through health insurance. Health insurance was proposed as one of the pillars of universal health coverage at the 58^{th} World Health Assembly in 2005 (WHO, 2005) and since then, several countries have developed policies and passed laws in its support. These international trends and in-country policy dialogues have resulted in making health insurance an aspiration for the Ugandan government, as a means to curb increasing out of pocket expenditures and provide more resources to the health system (MOH et al., 2012). However, it is still minimal with a very small proportion of the population participating in any health insurance programme.

Health insurance of any kind exists on a very small scale in Uganda, because of mainly two reasons; (1) roll-out bottlenecks such as the slow policy-making process and (2) several enrolment barriers for few urban and rural insurance players. Planning for social insurance and voluntary health insurance in Uganda dates back to 1995 (Basaza et al., 2013). In 2006, the government tasked the Ministry of Health to develop a National Health Insurance Scheme, that would first enrol civil servants and formal sector employees (Nabyonga Orem and Zikusooka, 2010). In 2008, a bill, authored by the Ministry of Health, was presented to the parliament, but due to opposition from the private sector (employers and insurance industry players) was not passed. A revised version was presented to and approved by the Cabinet in 2011 and was expected to be passed into law by 2013. However, the formal processes are, however, still ongoing and the scheme is far from realisation; a very slow process well documented by Basaza et al (2013)[7].

One of the reasons for the slow progress has been attributed to lack of consensus between the government and the existing private health insurance players on technicalities such as premium setting and payments refund channels (Khisa, 2014). In addition, there is no consensus within responsible government departments on how the scheme would be managed[8]. However, most importantly, there have been the questions of protection and affordability for the poor, the risk of further widening inequalities in health and incorporation of existing insurance systems (Nabyonga Orem and Zikusooka, 2010).

1.5.3.2 Coverage of private health insurance

In the absence of a state-supported health insurance scheme, private health insurance provides the only option for health insurance. Private health insurance schemes can be categorised into three categories. Category one is insurance companies that offer health insurance plans. The second category is made up of health membership organisations, generally run by private health service providers. Under

[7]Only in April 2017, the revised bill received a certificate of financial implications and will then be re-evaluated by the Cabinet and re-tabled before Parliament (Ainebyoona, 2017)

[8]For instance whether the national scheme would be managed by the ministry of health, ministry of finance of exist as an independent government parastatal organisation. The National Social Security Fund has previously disagreed with the plan to start the social insurance scheme in support of its own plans to provide health insurance benefits to its clients (Khisa, 2014)

these two categories, insurance cover is provided through employers and is operational in urban areas only and providers are profit motivated. The third category is micro and community-based health insurance schemes, which are described further in the next section.[9]

Data on total coverage of private health insurance are at best, scanty due to inconsistent reporting[10]. Carpenter and Kenward (2013) estimated conservative figures of about 460,000 people covered by private health insurance in 2012. Moreover, there is some considerable fragmentation in what is considered and thus reported as health insurance and what is not. For instance, Carpenter and Kenward (2013) mention that microfinance deposit-taking institutions (MFIs) also provide health insurance coverage to account holders estimated at 1.3 million people and yet these are outside the supervision of the Insurance Regulatory Authority.

1.5.3.3 Community-based health insurance in Uganda

All kinds of private health insurance schemes, except for CBHI, target urban populations, especially those in employment and with stable incomes. CBHI is therefore the only option for pre-paid health services for a large urban and rural population. CBHI in Uganda dates back to 1996 when the United Kingdom's Department for International Development supported establishment of a pilot scheme in south-western Uganda (Musau, 1999). At the time of this research, there were 22 individual CBHI schemes with a coverage of slightly over 141,000 individuals and operating in 17 districts (UCBHFA, 2014). These schemes include community-managed schemes, provider managed schemes and third-party managed schemes. Literature on CBHI in Uganda, regarding any issue such as enrolment, impacts, interplay with other health financing streams and other issues, remains scarce. Only two broad studies; Basaza (2011) and Twikirize (2009) both focused on determinants of enrolment in CBHI schemes in a qualitative manner. Their findings are quite mixed. Twikirize and O'Brien (2012) find that in regions where both free public health services and for fee private services, a larger proportion of the population preferred using private services through joining insurance schemes. They find that financial protection, quality of services and benefits that accrue to mutual assistance were the main drivers of households desire to enrol in insurance. The fact that with the alternative of free public services, households considered financial protection a main reason for insurance probably provides more credence to the inference that public health services were not in practice free, as has been found by Hunt (2010).

[9] Community-based health insurance and micro-health insurance are terms among the others used to define health insurance targeting the rural informal sectors (Donfouet and Mahieu, 2012). Across different countries, and contexts there might be some minimal differences. Here we use the terms synonymously.

[10] For instance, annual reports of the Insurance Regulatory Authority from 2011 to 2015, provide data for only 2 years (2011 and 2012) and only from insurance companies and not health membership organisations or micro insurance schemes

Another set of studies on enrolment in CBHI schemes are by Basaza et al. (2007, 2008, 2010). In this work, the authors confront the question why enrolment remains very low. Their main finding is that low information and understanding about CBHI by both service users and healthcare managers at district and national level was partly responsible for the dismal enrolment. Moreover, many health services managers believed the implementation of CBHI would be inconsistent with the government's free health services policy and hence broad policy support remained lukewarm. From the communities in which the schemes were operating, similar information and awareness bottlenecks inhibited enrolment Basaza et al. (2008). Low enrolment was further attributed to lack of trust between scheme managers and target populations, especially relating to previous experiences of fraud and dubious schemes and an inability to raise the financial requirements of membership Basaza et al. (2007, 2008).

A possible reason for the divergence in results from the two strands of research on CBHI in Uganda (that is, Basaza et al. (2007, 2008, 2010) and Twikirize and O'Brien (2012)), is the distinction between the CBHI schemes assessed. Basaza and colleagues bases their findings on third-party (non-governmental organisations) run schemes, which aim to formalise health insurance at the community level with non-profit motives. Twikirize and O'Brien (2012), on the other hand, study Kisiizi Hospital CBHI, a scheme which has important formative differences from other community and micro-insurance schemes . These CBHI schemes have distinct experiences with the communities in which they operate. For instance, the latter schemes build on social capital and existing trust in communities while the former require new ways of trust building in non-community institutions. In fact, Cecchi et al. (2016) find that introduction of third-party run CBHI was associated with a reduction in existing social capital and promotion of inequalities in communities.

By and large, health insurance, of any kind in Uganda, remains at a very small scale. The Living Standards Measurement Survey, which collects information on various social and economic areas and has been conducted in Uganda since 2009 dropped a health insurance module after very low response rates. In the first survey (2009/10), only 1.9 percent (55 out of 2,933 respondents) of the respondents had insurance and this reduced to 1.4 percent (37 out of 2,613 respondents) in the 2011 round of the survey. The module was omitted from the subsequent surveys. This study, therefore, aims at not only qualitatively understanding the determinants of enrolment and drop out from CBHI scheme but also build more knowledge using the largest scheme in the country, on pathways for scale-up of enrolment and later, draw linkages between health insurance and health outcomes, especially for children.

1.5.3.4 The study area: A brief history of Kigezi

This study used a case study of Kisiizi Hospital Community-based Health Insurance Scheme, a relatively large scheme in the rural communities of south-western Uganda. This scheme is the largest CBHI scheme in Uganda. At the time of this research, the scheme covered over 7,200 households and close to 40,000 people. In addition, the case study being rural gives an opportunity to focus on rural health care which usually has worse health metrics when compared to urban health care. In order to understand the case study, it is important to first give a brief historical landscape of Kigezi, in which the case study is situated. The research area in the south-eastern part of Kigezi sub-region, a highland area in south-western Uganda. Kigezi the borders the countries of Rwanda to the south and Democratic Republic of Congo to the West. According to Denoon (1972), the region occupies about 1900 square miles. The area is mainly highland with average altitude ranging between 2000 and 2500 metres above sea level. To the south-western part of the region is Muhabura ranges, reaching up to 4127 metres above sea level BakamaNume (2011). This region is inhabited by the Bakiga and Banyarwanda/ Bafumbira ethnic groups. The traditional social systems are decentralised in that social, political and economic organisation was engrained in small closely knit kin-relationships (Denoon, 1972; Edel, 1957). Historians have noted the inhabitants as "a classless society, as a people who lived as one independent class of peasant people who were not unified, had no tribal organisation and no formal authority" (Edel, 1957). Edel further suggested that communities were built on mutual respect derived from strong and reciprocal kin relationships and lineage systems. Very strong social ties existed between several households from the same lineage and in these strong networks existed, and obscure codes of conduct in which norms for authority and power were embedded (Edel, 1957).

Central to the lives of this society were egalitarian ideals, where helping others was held in high regard. Taylor (1962) summarised these values that the people's aspirations were to "have a plentiful supply of food and beer, many livestock and finally, the ability to dispense hospitality and fulfil traditional obligations to relatives and friends" (Taylor, 1962 in Turyahikayo-Rugyema (1976)). Edel further observed that there was "little apparent effort at accumulation" (Edel (1937) in Turyahikayo-Rugyema (1976). Turyahikayo-Rugyema (1976) observed a system of social reciprocity in which even the households on the peripheral of resources and trade still had access to goods and services through gift-giving, hospitality, and redistribution. All community members were expected to give gifts to their kinsmen and expected to receive gifts in return, as gestures of reciprocated hospitality. In instances where adherence to these social norms were not observed, there were repercussions that accrued such as refusal to join others at public gatherings. Repeated behaviour could attract strong sanctions including banishment from the village (Turyahikayo-Rugyema, 1976). It was therefore in the interest of every member of the community to adhere to such social norms for continued harmony.

It is through these reciprocal social support systems in which burial societies locally referred to as "engozi" are placed. [11] Katabarwa (1999) notes that they have existed for over 100 years. In these burial groups, every family has a right to be assisted if a member is ill as well as the responsibility to reciprocate assistance to other community members. Assistance can extend to non-health endeavours such as tilling land and other domestic chores (Katabarwa et al., 2000a). Membership in such groups was based on kinship and hence participation compulsory (Katabarwa, 1999). It is important to note that while burial groups have existed in Kigezi for hundreds of years, their emergency in other parts of Uganda has been recorded only recently especially in the wake of the HIV/AIDS epidemic (Jones, 2009; Mukiza-Gapere and Ntozi, 1995; Ntozi and Nakayiwa, 1999). This background is important to understand the origins of CBHI in Kigezi. Burial societies are the foundation of the Kisiizi Hospital CBHI scheme (Musau, 1999) and therefore central to this case study.

The region is currently composed of four local government districts with a combined population of about 1.3 million people [12]. With a history of a high population growth rate, the region has one of the highest population densities in the country of over 270 people per square kilometre, which is above the national average of 173 people per square kilometre (UBOS, 2015). People are mainly peasants, with over 80 percent engaged in subsistence agriculture (UBOS, 2009, 2012, 2013). Estimates from the 2002 national population and housing census indicate that the region had more than a third of the population living below the poverty line (Emwanu et al., 2007) though recent estimates from a 2016 national household survey indicate that this has reduced to 19.5 percent (UBOS, 2017). Using a multi-dimensional measurement of poverty, it was estimated that more than 79 percent of the population were deprived in at least three of the ten dimensions of poverty assessed (Levine et al., 2014).

In certain aspects of health, this region is better than other regions of Uganda, partly due to its topographic disposition and partly due to investments in health infrastructure over time. For instance, the region, like other mountainous regions of Uganda, has one of the lowest malaria prevalence rates in the country (Yeka et al., 2012). In terms of the health infrastructure, while one third of districts in Uganda do not have a hospital (MOH, 2014), each of the four districts in Kigezi has two general hospitals and several smaller health facilities such that the population health facility ratio of 5000 people per health facility is considerably better than the national average of 9000 people per health facility. It is not surprising, therefore,

[11] The word *"engozi"* can be loosely translated as stretcher. Probably the correct local name for burial groups is *"tweeziike"* which can be loosely translated as "let us bury ourselves". These two words are generally used to refer to the same group. These are groups based on kinship and or village membership in which every member of the village is obliged to belong. In the event of sickness or need of special health attention such as delivery, the group members provide rudimentary ambulance (stretcher hoisted on men's shoulders) to a local health service provider. In the event of death, group members support the bereaved household through provision of burial materials. These groups are maintained through modest financial and in-kind contributions of the members. Such groups have existed for hundreds of years and continue to be a central component of village social support and social network structure.

[12] At the time of fieldwork, the three districts served by Kisiizi hospital were Rukungiri, Kabale and Kanungu. They have now increased after the creation of new districts in 2016

that given the history of the area and health development trajectory, the region has several CBHI operating in all districts in the region, including the largest, Kisiizi Hospital CBHI scheme.

1.5.3.5 Kisiizi Hospital Community Health Insurance Scheme

Background: In 1995, the Community Health Financing Project started at the Ministry of Health, with funding from the Department for International Development(United Kingdom). At the time, the government's health financing policy was a cost-sharing system where service seekers paid a portion of user fees. The project's mandate was to pilot community financing schemes across the country, as a source of supplementary health system financing (Derriennic et al., 2005). A pilot scheme was started in 1996 in cooperation with Kisiizi hospital, a rural community hospital at the congruence of Kabale, Rukungiri and Kanungu districts. The communities already had organised burial groups which were leveraged for recruitment of households and popularising of CBHI[13]. By 2000, the scheme's recruitment was composed of 32 burial groups comprising of 1,400 households (Ranson and Bennett, 2002).

At the end of the pilot in 2002, a health insurance promotion group, Microcare Limited, was contracted by the hospital to manage the scheme (Greyling, 2013)[14]. The new management facilitated an enrolment drive through expanding the package of care and support services. The new management's actions were building on recommendations of Musau (1999) to introduce more "aggressive marketing", improve financial management and risk assessment to make the scheme sustainable. The new package of care expanded from outpatient and inpatient care to include surgical care and maternity care of all kinds, physician-provided out-patient care, laboratory, radiology and diagnostic testing; basic dental care, eye care and most importantly at the time, first-line treatment of HIV. Another important feature of the improved benefits package was the investment in preventive health care for common illnesses such as malaria and other water-borne diseases.[15] By 2009, the scheme covered almost 35,000 individuals. After the collapse of Microcare Limited

[13] Promotion of CBHI through burial groups seems to have been a standard process for pilot projects. One of the first recorded CBHI scheme, the Bwamanda scheme in Democratic Republic of Congo was also a partnership with a local mission hospital and enrolment was largely associated with existing village groups (Criel and Kegels, 1997; Criel et al., 1998). Burial societies have also been foundations of informal insurance networks in Tanzania and Ethiopia (Dercon et al., 2006)

[14] In October 2002, after the withdrawal of donor support and policy change to tax based free healthcare, the hospital appointed Microcare to handle all insurance related business. Microcare had been founded in 2000 as a not for profit organisation focussed on providing insurance services to poor and marginalised communities. In 2004, it registered as an insurance company and by 2007 had become the country's fourth largest insurance company. However, a series of internal and external bottleneck led to its collapse in 2009 (Greyling, 2013).

[15] See http://siteresources.worldbank.org/EXTFINANCIALSECTOR/Resources/282884-1239831335682/6028531-1239831365859/Harmeling_Case_UgandaMicrocare.pdf

in 2009 for reasons not related to its management of the Kisiizi scheme[16], the Kisiizi hospital took over full administration of the scheme, making it a fully provider-based CBHI scheme.

Enrolment: As at the beginning of the scheme, enrolment is still based on membership in burial groups. Burial groups/engozi are typically composed of households from the same or neighbouring villages and members are likely to have close kin relationships. They can be as few as 20 households and as large as 200 households. Groups are self-managing, with their own leadership structures typically composed of a chairperson, a treasurer, and secretary. The scheme does not have any influence as to how this leadership team is selected. For some groups, the leadership team hardly changes and for others, selection of new leaders happens periodically. Group leaders are responsible for the premium collection, updating of their membership and enrolment registers and transmission of information between the scheme and group members.

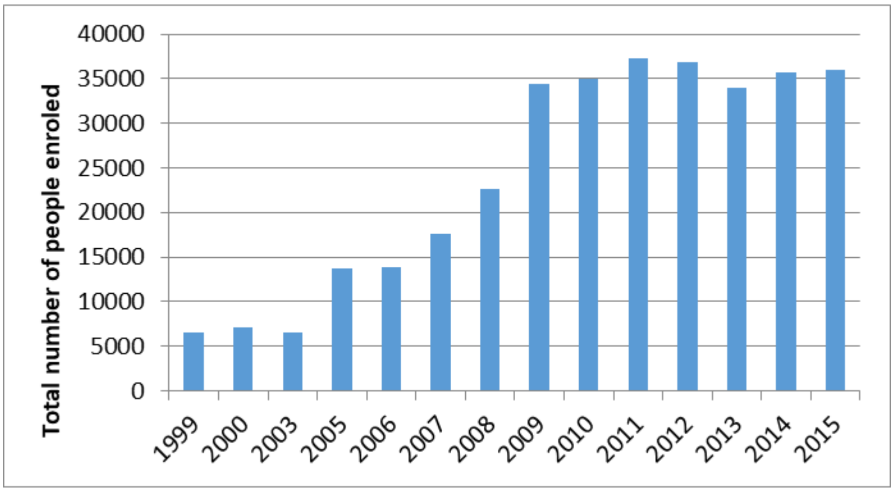
The scheme has since grown both in terms of its geographical and numerical reach. Currently, the scheme is the single largest non-profit insurance programme in the country with over 7200 households forming its membership across five districts in south-western Uganda. The number of individual members registered in the scheme is close to 40,000 from 202 burial groups[17]. There are three main conditions on eligibility for enrolment. The scheme management believes these conditions control moral hazard. The first one, pertaining to groups is that for a group to have its members enrolled, it must have a minimum of 20 households and if a group has 30 or fewer households, all have to be enrolled. The second condition is that for larger groups, at least 60 percent of the households have to enrol (Carrin, 2003). The insurance scheme does not put an upper bound on the size of groups however, 60 percent should be more than 30 households. The third condition, in regard to households, is that for a household to enrol, all household members have to enrol. This is referred to as the "full household enrolment" requirement. This implies

[16] Media reports (e.g see http://www.observer.ug/news-headlines/3568-medical-insurance-regulator-colludes-to-kill-microcare) indicate that there might have been collusion between the regulator and service providers under possible influences from competitors. Auditors appointed by the regulator declared the company unfit for providing insurance services which led to withdraw of the license. However, a study undertaken by the International Labour Organisation through the Microfinance Innovation Facility (Greyling, 2013), found that among the reasons for collapse of the company was poor tracking of claims from individual health providers and clients, lack of strict monitoring and relaxed selection for service providers and poor alignment of insurers interests with those of services providers and clients, all of which might have resulted in collusion between service providers and clients. A recent high court ruling rejected all the company's claims and ruled in favour of the insurance regulator (see https://www.ulii.org/ug/judgment/commercial-court/2017/47/). However, it should be noted that these problems were only limited to the company's urban operations which would have excluded the Kisiizi scheme.

[17] Based on communication with scheme managers

that for a household to be enrolled, all household members have to be included as beneficiaries of the scheme [18]

Figure 1.5: Enrolment in Kisiizi CBHI



Source:Blanchard-Horan (2007); Musau (1999) & field notes.

Premiums: Early on, premiums were collected on a quarterly basis through the groups. Currently, premiums are collected on an annual basis. Premiums are based on the size of the household, and range from UGX 10,000 (US$ 3) to UGX 30,000 (US$ 9), as shown in Table 3.[19] There is an option known as ”green card” which facilitated members to access a broader range of services such as the use of hospital private rooms instead of general wards. Co-payments range from UGX 2,000/= (US$ 0.6) for outpatient consultation to UGX 50,000 (US$ 14.7) for surgeries. Newly enrolled members pay 90 percent of the hospitalisation fee if they use hospital services in a period less than 12 months after the time of enrolment. This is implemented as a measure for controlling moral hazard. Saving for premiums payments can be difficult in rural areas. Many of the enrolled groups operate special health savings accounts and/or broader village lending and saving arrangements, which enable members to save and meet their household specific premiums. For this reason, that drop out is considerably low in comparison to other schemes across developing countries.

[18] One exception is groups enrolled in the CBHI scheme that are not based on membership in a burial group. An example of such groups church-based support programs for orphans and other vulnerable children, which only have individual children supported by the programs as beneficiaries, rather than the entire families where such children live. Of all the 202 groups at the time of the survey, only 2 groups were of such classification; a church-based support group for orphaned children and a hospital and schools staff association group. Partial insurance, where some household members are enrolled and others are not exists in other insurance schemes such as the Ghana scheme (Kusi et al., 2015a).

[19] Average annual exchange rate of US$ 1=3400 UGX in 2015. According to the 2012 National Household Survey (UBOS, 2014a) average annual household incomes for Kigali region were Uganda shillings 4.1 million, derived from reported monthly income of Uganda shillings 343,000. This implies that total premiums for a household of 11 members would be 2.4 percent of total annual household income and 1.4 percent of household income for a household of 2 members. Using the 2016 survey (UBOS, 2017), annual premiums are equivalent to 1.8 percent of average annual household incomes for a 11 member household and 1 percent for a 2 member household.

Table 1.3: Premium structure

No of household members	Premiums (UGX) per head	Equivalent in USD
Green Card	30,000	8.8
2	28,000	8.24
3-4	14,000	4.12
5-7	11,000	3.24
8-11	10,000	2.94
>=12	15,000	4.41

Source: Scheme records

Benefits package: Over the years, the benefits package has expanded, specifically to include coverage for some chronic conditions. Table 4 above gives an overview of the benefits package. One important feature of this scheme regarding benefits is the timing of coverage. In order to further control moral hazard, members received full coverage once they have been in insurance for at least 1 year. Once a household member is ill within only one year of enrolling, insurance covers only 10 percent of the cost of hospitalisation. This is a considerably long waiting period in comparison to other schemes, for instance, the CBHI scheme in Nigeria where the waiting period was only 36 days before receiving full coverage (Bonfrer et al., 2015). Typically, insurance package covers basic primary care, maternity care, surgeries, and outpatient and inpatient services. Outpatient services for chronic illnesses and substance abuse related illnesses and injuries are excluded. Maternity care is subject to attending at least 4 ANC visits, of which the first one has to be at Kisiizi hospital; Care for chronic illnesses is subject to attendance of special clinics and adherence to the prescribed treatment plan; referrals are not covered. The package also covers 50 percent of cervical cancer treatment costs.

Previous studies about the Kisiizi Hospital CBHI scheme: It is understood that so far, only three studies have studied the Kisiizi CBHI scheme at a considerable level of academic detail. Blanchard-Horan (2007), uses qualitative methods to explore malaria treatment behaviour of members and non-members of community insurance plans. The researcher found that members of insurance schemes were more likely to seek hospital care earlier than uninsured counterparts and had significantly less financial barriers to access. Dekker and Wilms (2010) use quantitative methods to explore the relationship between health insurance and other risk coping strategies during sickness. Their study established that insured households spent considerably less out-of-pocket expenditures and sold fewer assets for medical expenses compared with their uninsured counterparts. The third study is by Twikirize and O'Brien (2012) who undertook a qualitative analysis of factors influencing the enrolment in CBHI. The main findings of this study are already discussed in this thesis

1.6 Sampling strategy and data collection

This study was purposively undertaken in the area around the Kisiizi hospital, which included parts of districts of Kabale and Rukungiri.[20] As mentioned earlier, Kigezi sub-region generally has a higher health facility population ratio, implying that people close to government health facilities might be inclined not to enrol in insurance since they have access to free health services in government facilities. And given that the quality of public and private health services differs in rural Uganda (Ssengooba et al., 2002) and since controlling for hospital quality would entail bigger studies, a smaller geographical area of study was devised. The research area was limited to within a close proximity to the insurance providing hospital to the extent that communities have limited incentive to alternative government health facilities farther from them. In consultation with senior health officers from the two districts three sub-counties Nyakishenyi and Nyarushanje in Rukungiri district and Kashambya in Kabale district, all within 15 kilometres from Kisiizi hospital were selected for the survey. The three sub-counties had, according to the 2014 national population census a total population of about 105,600 people in 23,500 households (UBOS, 2014b).

Using an online sample size calculator[21], a population representative sample of 383 households was defined. A 5 percent precision rate, which corresponds to 95 percent confidence interval is incorporated in the algorithm. Since this is the first ever survey to establish enrolment status of this scheme, a 50 percent prevalence rate was assumed. A further 85 percent response rate is included. A total sample of 440 households was therefore identified as the appropriate sample size.

In order to select these households, a multi-stage simple random sampling strategy was employed in the three sub-counties. The three sub-counties have a combined 23 parishes and 313 villages. Through local administrative leaders, all 23 lower level local government leaders[22] were invited to a day's sampling workshop, however, only 15 turned up for the workshop. Eight parishes and their villages for which the leaders did not attend were excluded at this stage. During the workshop, the purpose of the research and necessity of leaders' participation in sampling and guiding the data collection team were elaborately explained to the leaders.

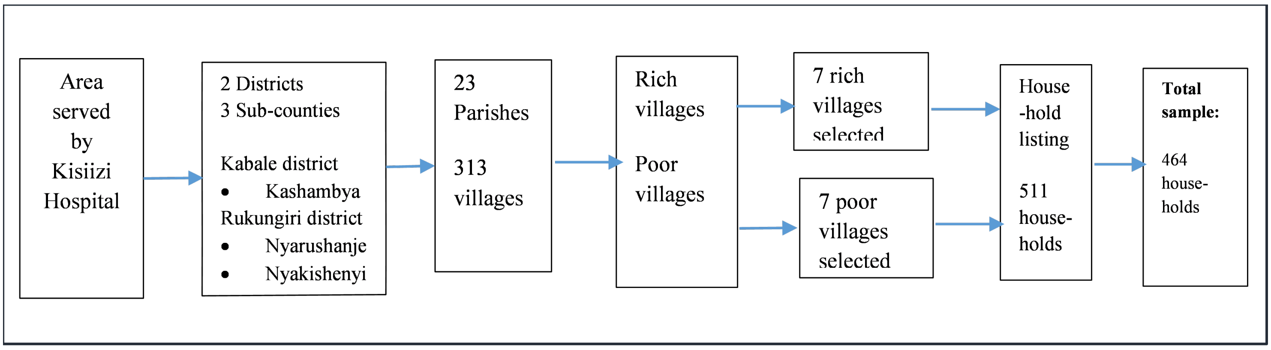
The leaders who attended the workshop represented 174 villages and 15 parishes. For each parish, the leaders were requested to categorise the villages in two categories; rich and poor villages. A village was considered rich if it had at least two of; (a) a road, (b) a market and (c) a school, plus a subjective assessment of whether the leaders thought that a particular village was poor or rich. From this categorisation, 70 villages were categorised as rich and 104 villages categorised as poor. All village names were written on papers and placed in raffle boxes from which 14 villages were randomly picked, seven for each category (poor and rich).

[20]The hospital is 40 kilometres from the district headquarters of Rukungiri district and about 65 kilometres from the district headquarters of Kabale district.

[21]Available at http://sampsize.sourceforge.net/iface/#min

[22]At local government administrative level lower than a sub-county is parish, which is comprised of several villages. We therefore invited parish leaders known as "parish chiefs".

Figure 1.6: Simple random sampling strategy



After selecting the villages, a pre-field visit was conducted in each of the selected villages. The village leader in each village was asked to list all the households in the village which had at least one child above six months and less than 5 years of age. The household listing in all sampled villages returned 547 households. Data collection was undertaken from September 2015 to March 2016. During data collection, some listed households were excluded because of inconsistencies regarding ages of the children. Some listed households had children found to be less than six months or more than 5 years of age. The exclusion of these households resulted in a 10 percent discrepancy between the number of listed households and the actual sample. Overall, a population representative sample of 464 households was included in this survey. Data collection utilised a Computer Assisted Personal Interviewing (CAPI) platform. CAPI platforms have recently emerged as efficient and cost effective tools for routine data collection, compared to conventional paper-based data collection methods (Caeyers et al., 2012).

The survey tools included: a) a household demographic module which collected information on household occupancy; b) a child and maternal health module which collected information on health care seeking behaviour for mothers and children; and c) a nutrition module which collected information on household food availability and intake. Other modules addressed: d) household social and economic welfare using durable assets holdings and other endowments in agriculture, water and sanitation, and housing; and e) health insurance and social connectivity with information regarding household insurance status, group membership and participation, and knowledge of insurance such as premiums and benefits package. In line with emerging tools for understanding enrolment in community insurance in sub-Saharan Africa, the survey incorporated a detailed module on perceptions about several aspects of health insurance. In order to get a better understanding of health insurance, birth registry data recorded in birth registers in health facilities with functioning maternity facilities were also collected from six health facilities. The data are presented as part of summary statistics in Chapter Two of this thesis but are not used in further estimations

Table 1.4: Sampling Frame

	Sub-county	Parish	Village	Targeted Sample	Sample Outturn	% of out turn
1	Nyakishenyi	Ngoma	Kacence	56	51	91%
2	Nyakishenyi	Bikongozo	Bikongozo	25	18	72%
3	Nyakishenyi	Bikongozo	Kayanja	33	21	64%
4	Nyakishenyi	Kafunjo	Kagasha	18	16	89%
5	Kashambya	Kafunjo	Nyakarambi	43	49	114%
6	Kashambya	Kafunjo	Kabisha	45	47	104%
7	Kashambya	Rutengye	Nyamishamba	36	23	64%
8	Kashambya	Rutengye	Kazooha	48	48	100%
9	Nyarushanje	Ndago	Nyakatokye	24	18	75%
10	Nyarushanje	Burora	Kyaruhotora	58	53	91%
11	Nyarushanje	Bwanga	Shumba	51	36	71%
12	Nyarushanje	Kisiizi	Rusa	41	29	71%
13	Nyarushanje	Ruyonza	Kimbugu	30	37	123%
14	Nyakishenyi	Kahoko	Izinga	38	18	47%
	Total			546	464	85%

1.7 Ethical considerations

The study underwent careful considerations to protect the physical and psychological welfare of all respondents by undergoing thorough ethical review processes. The study was approved by the Centre for Development Research, University of Bonn Ethics Review Committee in accordance with the University of BonnŠs research requirements. In Uganda, the study protocol was assessed by Mengo Hospital Ethics Review Board and further approved by the Uganda National Council of Science and Technology (UNCST). A research certificate SS-3936 was issued. The study plan was also reviewed and approved by Kisiizi hospital ethics and research committee. A memorandum of understanding was signed between the researcher and the hospital administration. Due to the sensitive nature of some of the discussion modules covered in the survey, all interviewing was undertaken by trained female research assistants.

1.8 Some assumptions and caveats of this research

It is important to note that this research is based on a number of assumptions. Supportive information is provided on why these assumptions should hold. The effort is also made to point out a number of questions which these assumptions might raise and for those that might be within the scope of this research, the effort is also made to respond to them. It would be worthwhile for future researchers interested in CBHI in Uganda to consider following up on some of the outstanding questions.

The first assumption is the unitary household assumption. The unitary household model, as opposed to a collective household model, treats the household as a single production and consumption unit, where decisions about welfare are taken at a household level. A unitary household framework assumes that the utility derived from a household's income does not depend on the income distribution of members of the household (Doss, 2013). The household is one single unit where all sub-units have similar preferences and that intra-household decision making and resource allocation achieves efficiency. This implies that in times of shocks, members of the household have the same consumption smoothing patterns and in times of investment, they make Pareto efficient investments. It is further assumed that the decision maker in the household is altruistic in that he/she cares for the welfare of all the household members equally. This is indeed a profound assumption. While this assumption has been central to development economics in relation to households, a substantial amount of work, for instance, Dercon and Krishnan (2000), Haddad et al. (1997) and Robinson (2012) has challenged it. For instance, women's consumption smoothing during shocks is lower during times of shocks (Robinson, 2012) and so are investments during times of investing (Udry, 1996). However, the unitary household assumption is not completely untenable. In some particular instances, households can achieve near Pareto efficient allocation of resources, for instance, nuclear families in Burkina Faso (Kazianga and Wahhaj, 2017) and efficiency can also be improved through participatory decision making (Lecoutere and Jassogne, 2016).

Therefore, for a researcher to choose between the two household models, there is a necessity to back-it-up with qualifying information on the environment in which the intervention of interest operates (Alderman et al., 1995; Thomas, 1997). To qualify this assumption for this work, it is noted that most of the research that disqualifies this assumption (wider research on collective household models) is concerned with the distribution of resources within the households which in turn has implications on consumption smoothing or investment decisions. The central question of such work is therefore on who controls income (Alderman et al., 1995). Cognisant that who controls income is an important issue, this research does not directly deal with income distribution in the household because enrolment in CBHI is at household as a unit and not individuals. The framework of this case study, therefore, diverges from what one might see in other CBHI schemes, the existence of partial insurance - where some household members might be insured and others not insured (Kusi et al., 2015a,b). Moreover, the framework of our case study also implies that after enrolling in CBHI (reminiscent of a public good) there is no rivalry and excludability in use for any individuals of the enrolled households. In other words, utilisation of insurance by one household member does not affect the utilisation of insurance by another. Therefore the unitary household assumption should hold. However, in the possible future extension of this research, one might look into household income distribution. For instance, if it is the husband's or mother's income that is more correlated with CBHI enrolment. Because of data limitations, it is not possible to elucidate this from what was collected.

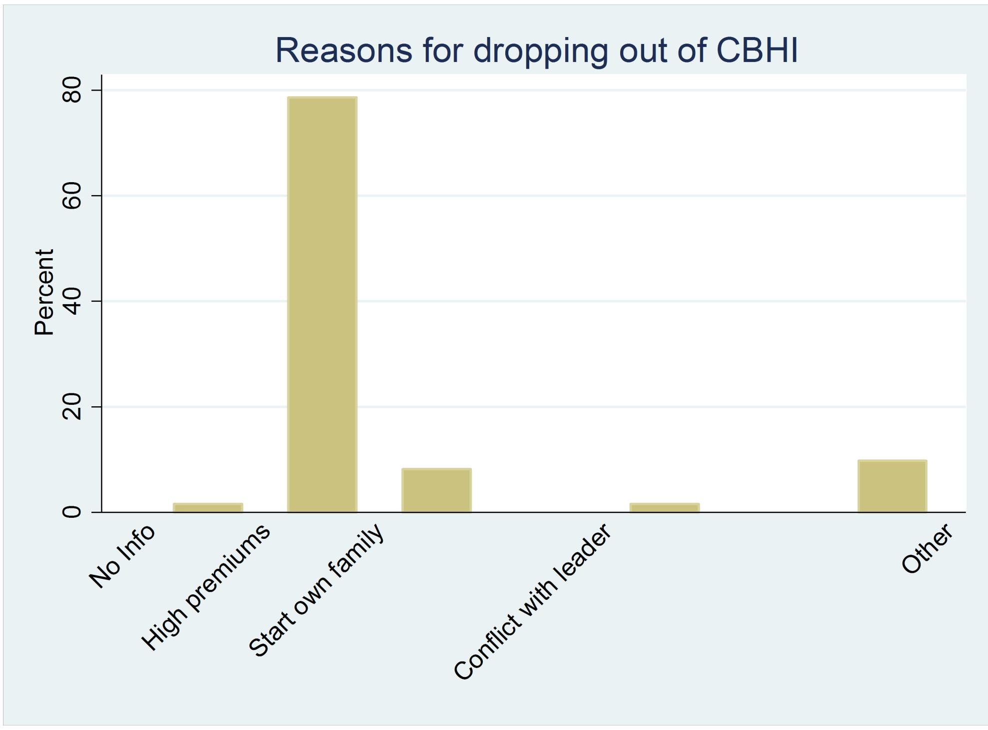
The second assumption is that group leaders exhibit the same behaviour for all their members, without favouring some over the others based on their social or economic status. This assumption is posited because of two reasons. First is that the data collected about groups is not sufficient to provide an adequate base to observe intra-group dynamics and within group behaviours on the decision to enrol, stay enrolled, fail to enrol or enrol and drop out of CBHI. However, in all the subsequent chapters, several group covariates are controlled for and so some group influences are captured. The second reason is that it is believed that these group dynamics might be of limited importance because of the nature of groups dealt with in this study. In group-facilitated health insurance, group leaders perform a function related to insurance agents by providing a channel between the clients and the insurance provider. In this case, burial group leaders' responsibility is to collect premiums from their group members and deliver them to the hospital, the insurance provider. Costs associated with collecting premiums from poor households versus rich household might lead to more focus on the richer households for whom it would be less costly to collect premiums from, potentially leading to adverse selection.

This kind of adverse selection might be revealed by high membership rates of the richer households, low membership of poor households or high dropout rate from the mostly poor households. Adverse selection might also happen if high-risk households are favoured or self-select into insurance more than low-risk households (Parmar et al., 2012). However, this behaviour is not expected from burial group leaders because of three reasons. The first reason is that premiums are collected in a substantially long period, spanning several months. Through a mechanism of health savings accounts, households deposit a principal amount for health savings and these are allowed to grow through lending and accruing interest. Premiums for the oncoming year are therefore comprised of monthly savings, initial savings plus accrued interests. In this way, all members have a potentially reduced burden of saving for the full annual premiums. This is not to suggest that households do not have challenges in raising premiums. Using the average household size of 5.7 individuals, it was observed that total household premiums were equivalent to 12 percent of annual income for the poorest quintile and only 3 percent of annual income for the richest quintile. Furthermore, reviewing the reasons why households dropped out of CBHI, it was observed that failure to afford premiums was the main reason for drop out.

The aim of this narrative is to show that leaders play an almost negligible role in the decisions of households to enrol and so the assumption that leaders do not favour some people should hold. It must be pointed out, however, that it is not claimed that adverse selection is completely eliminated. Establishment of the presence of this dimension of adverse selection, if any and the pathways through which it is manifested might be an issue which further research might be interested in investigating.

However, as a control measure against possible adverse selection, a number of conditions are in place. These are full household enrolment policy, considerably long waiting period and the group requirement of 60 percent of the households if the group is large and all households if the group is less than 30 households. These

Figure 1.7: Reasons for dropping out of CBHI



Source: Survey data

conditions were put in place in the early stages of the scheme in 2001 (Carrin, 2003). In reality, most groups perform much better than simply meeting these minimum requirements. Anecdotal information from the scheme staff suggests that enrolment rates in CBHI-participating burial groups are as high as 95 percent or more. Detailed data per group is not available to conclusively support this claim. However, on the basis of the collected data, and using the stated number of households in a particular burial group as the burial group size, it was found that in all CBHI-participating burial groups, enrolment was on average 96 percent. An average of only 4 percent (range 1 to 8 percent) of members reporting participation in 2010 reported dropping out in 2015. The overall non-participation in CBHI was found to be mainly related to financial reasons rather than group leadership.

Finally, taking from a previous intervention on the prevention of river blindness, in which the influence of burial groups is regarded highly as a success factor (Katabarwa et al., 2010a, 2004, 2000a), there were no indications that leaders in the burial groups treated members any differently. For these reasons, it is believed that leaders are equally egalitarian to all members of the groups they lead.

The third issue to put into consideration throughout this thesis is that what is analysed are the health outcomes of only one person per household, who is the youngest child and under-five years. Data was collected data on the youngest child because of the possibilities of recall biases regarding information on older children, which are common in health-related surveys (Clarke et al., 2008; Kjellsson et al., 2014; Manesh et al., 2007). Perceived recall biases can be reduced by choosing shorter recall periods for the respondents though this is at the cost of the reduced amount of information one might receive (Kjellsson et al., 2014). The implication of this choice taken (shorter recall period) is that it is assumed that, at a household level, the result of a particular under-five child also applies to an unmeasured under-five older sibling. This also assumes that there is no accounting for gender segregation at the household level.

1.9 Further organisation of the dissertation

The rest of this thesis is organised as follows. Chapter Two responds to question one by providing a quantitative assessment of the determinants of enrolment of in CBHI in rural Uganda. The chapter first reviews literature from other countries which largely leans on the finding that household socioeconomic conditions and having the right quantity and quality of information are important for enrolment decisions. Logistic and Ordinary Least Squares (OLS) regressions are then undertaken and odds ratios and coefficients of the determinants of enrolment and renewing CBHI membership are presented. The chapter further investigates the influence of perceptions in the decision to enrol and remain enrolled, an issue that is increasingly relevant in CBHI interventions. Chapter Three aims at responding to question two in which the impact of CBHI on child stunting, a very important health outcome for under-five children is analysed. In this chapter, a novel Instrumental Variable (IV) approach that combines both the insurance status of the household and the insurance intensity of the household measured by the number of years a household has been in insurance is applied. -In this way, the analysis not only estimates the impact of insurance status but more so the results are interpreted in reference to the intensive margin - the effect of an additional year in CBHI on child's stunting profile.

Chapter Four then uses another robust method, inverse probability weighting on the propensity score to study the impact of CBHI participation on household's utilisation of preventive health services and home-based strategies. The method is robust to facilitate controlling for the observable determinants of CBHI status in order to isolate the effect of CBHI. It permits the creation of a credible control group composed of households who have the same probability of being in CBHI but have different CBHI statuses. Finally, Chapter Five presents some conclusions and limitations of the research. More importantly, draws some policy implications for CBHI at a time like this when Uganda is undergoing some health insurance reforms.

CHAPTER

TWO

WHAT DETERMINES ENROLMENT IN AND RENEWING OF COMMUNITY-BASED HEALTH INSURANCE IN RURAL UGANDA?

2.1 Introduction

The 2010 World Health Report (WHO, 2010) suggested that apart from the availability of and equitable use of resources, the other barrier to universal health coverage was over-reliance on direct payments for health care, which increased catastrophic expenditures to receive health services. As far back as 2007, it was estimated that as many as 150 million people faced catastrophic health expenditures and 100 million people were pushed into poverty annually due to such health-related payments (Xu et al., 2007). Poor households are more likely to borrow and or sell their household productive assets when faced with such health payments (Kruk et al., 2009). The same WHO report recognised the role of CBHI in achieving universal health coverage in developing countries. It suggested that countries should aim at "longer-term plans for expanding prepayment and incorporating community and micro- insurance into the broader pool" and that "voluntary schemes, such as community health insurance or micro insurance, can still play a useful role where compulsory sources provide only minimal levels of prepayment" and "...can also be an institutional stepping stone to bigger regional schemes, which in turn, can be consolidated into national risk pools"(WHO, 2010). Researchers and policymakers equally suggest that CBHI is an important building block for health systems financing and for broader pathways to universal health coverage, especially in developing countries (Agyepong et al., 2017; Bennett, 2004; Wang and Chen, 2012; Wang et al., 2012).

Influenced by high levels of international attention and growing support at multiple levels, CBHI popularity and practice has increased in many developing countries in Africa, Asia and Latin America (Dror et al., 2016). CBHI has indeed transformed the health landscape of several developing countries. For instance, a government-supported scheme in Rwanda, piloted in 1999 (Schneider, 2005), covered over 90 percent of the population by 2010 (Lu et al., 2012). In Ghana, the national health insurance scheme started in 2004 and building on existing small mutual aid schemes had enrolled 40 percent of the population by 2016 (Kotoh and Van der Geest, 2016). In Uganda, CBHI scale up has been observed, increasing from one pilot scheme in 1996 (Musau, 1999) to 21 schemes covering over 140,000 people in 2014 (UCBHFA, 2014) The determinants of enrolment in CBHI can be varied and are often contextualised to individual schemes and countries due to different legal and policy frameworks. However, a number of reasons have been summarised in a recent systematic review (Dror et al., 2016), which include: socioeconomic reasons that enable affordability, information about the scheme concerning benefits packages, and how target populations build trust in the schemes, the nature and quality of service providers included, and the overarching policy and legal environment.

For the Ugandan setting, though there has been some growth (like the number of schemes), enrolment has remained low. Previous qualitative studies have suggested mixed evidence of why enrolment has remained minimal. Lack of trust in the scheme managers and service providers and lack of adequate information as bottlenecks to enrolment are cited bottlenecks (Basaza et al., 2007, 2008). However, Twikirize and O'Brien (2012) show pockets of popularity. All these studies are of qualitative nature. This study, therefore, seeks to add on this thin understanding of the determinants of enrolment and continued participation, in a quantitative manner. This study is not only important in deepening the understanding of why households enrol in CBHI in Uganda but also comes at a time when Uganda is about to start a national health insurance scheme. Though the national health insurance scheme will be targeting first, civil servants and formally employed people, it has a provision for integrating CBHI schemes at a later time. This study, therefore, comes at a crucial policy juncture to understand reasons for enrolment and pathways to scale-up.

Logistic and Zero-Inflated Negative Binomial (ZINB) regressions were applied on a sample of 464 households from 14 villages in Kabale and Rukungiri districts in south-west Uganda. Odds ratios and incident rate ratios are reported for the two regressions respectively. Precisely, these were communities in which the Kisiizi Hospital CBHI scheme has a presence. Results reveal significant social network influence, from belonging to a dominant religion, to membership in large size burial groups and knowledge about the scheme as important predictors of enrolling in CBHI. It was established that child and mother's age, household size and size of the burial group a household belonged were important predictors of staying/ renewing CBHI membership. For both enrolling and staying in insurance, the number of burial groups participating in CBHI in a village was a highly predictive factor. The Kisiizi CBHI scheme, on which the assessment is based, is different due to the manner in which existing burial groups play a central role in mutual insurance functions (Katabarwa, 1999). This feature is important as it facilitates enrolment in CBHI and also groups provide extra mutual insurance. However, other schemes in the country and other countries do not have this feature so the results should be interpreted with this in mind.

The rest of this chapter is organised as follows. In section 2.2, is a review literature on enrolment in health insurance for the poor (including CBHI) across developing countries. The theoretical and empirical approach to this analysis is then discussed in section 2.4 and section 2.5 provides the descriptive and empirical results. Conclusions and some recommendations are made in section, 2.6.

2.2 Enrolment in health insurance in developing countries.

Whilst health insurance grows in popularity across many countries, enrolment remains relatively low in the target communities, especially when there are no subsidies for enrolment or when there are no particular laws that compel enrolment. By and large, less of the target population enrol and remain participating in respective insurance schemes. Early research from West Africa suggested enrolment rates ranging from 1 to 10 percent of the target population (De Allegri et al., 2009) but more recent findings elsewhere report enrolments of up to 37 percent of the target populations in some regions (Mebratie et al., 2013).

Throughout the literature, in countries where insurance is completely voluntary, participation rates are low. For instance, the much-studied voluntary schemes in Nouna district of north-western Burkina Faso, reported an enrolment rate of only 6.3 percent (Dong et al., 2009) while in India, participation rates ranged from 15 to 30 percent in the voluntary schemes in the Uttar Pradesh and Bihar (Panda et al., 2014, 2016). Schemes in East Africa are reported to afford between 1 to 12 percent enrolment rates (Basaza et al., 2009; Borghi et al., 2013; Kimani et al., 2012, 2014). In countries with voluntary participation, reaching up to 30 percent of the target population can be considered high coverage. In Sudan, the country's voluntary scheme provided coverage to 37 percent of the target population in 2014 (Herberholz and Fakihammed, 2016). Initial enrolment (first year of implementation) rates in Ethiopian pilot schemes reached 45.5 percent. However, this can be taken with caution as at least 10 percent of the enrolees expressed some coercion from village leaders to join the scheme (Mebratie et al., 2015b).

However, in countries where there is either substantial subsidies on insurance premiums or where governments have passed laws to compel enrolment, participation levels are much higher. For instance, in China, the New Cooperative Medical Scheme, started in 2003 with strong government support (Dib et al., 2008) reached 95 percent of the rural population by 2012 (Marten et al., 2014). In Rwanda, a national health insurance law facilitated enrolment in the community health insurance scheme to near-universal coverage levels in less than a decade (Lu et al., 2012; Makaka et al., 2012; Nyandekwe et al., 2014). In India, the government-supported Rashtriya Swasthya Bima Yojana provided coverage to 51.6 percent of the rural poor (Nandi et al., 2013) while the Ghana National Health Insurance Scheme was providing coverage to 40.3 percent of the population by 2016 (Kotoh and Van der Geest, 2016). In all these countries, the common denominator was government-led insurance reforms and subsidies. This corroborates the finding by De Allegri et al. (2009) that poor legislative frameworks in the majority of the countries hampered possible scale up and enrolment.

Apart from legal and policy bottlenecks, limited access to the right information is another bottleneck for enrolment (Dror et al., 2016). Availability of sufficient and credible information facilitates perception formation about whether to enrol or not. The last couple of years have therefore seen more literature focusing on perceptions of households and communities regarding decisions to enrol, quality of services and conduct of health workers among other issues. Jehu-Appiah et al. (2012) studied the influence of perceptions in health insurance enrolment decisions in Ghana. They found that perceptions on premiums, attitudes of health care workers and pressure from community peers negatively influenced enrolment while the quality of care, convenience financial protection, and benefits package were associated with enrolment. There have been other studies considering the influence of perceptions in Ghana

A crucial determinant of enrolment, keeping enrolled or dropping out of CBHI is social capital. (Donfouet and Mahieu, 2012; Mladovsky and Mossialos, 2008; Mladovsky and Ndiaye, 2015; Mladovsky, 2014) Social capital is simply a measure of how community members are integrated together, mutually depend on each other and how they also construct social relationships with authorities (Green and Haines, 2015) or rather norms and networks that enable people to act collectively(Woolcock and Narayan, 2000). The understanding is that households with a better social capital holding (wider networks and influence on their communities) are more likely to utilize insurance opportunities (Donfouet et al., 2011; Mladovsky, 2014) and that the lack of social capital, such as being excluded, could determine limit others especially the elderly, poor and marginalised from enrolling in health insurance schemes (Criel et al., 2014; Parmar et al., 2014). However, while lack of social capital might limit enrolment in CBHI, introduction of CBHI might destabilise existing social capital especially when CBHI operates outside of existing community social structures and fails to include extremely vulnerable sections of the community (Cecchi et al., 2016).

The success of health insurance is not only based on adoption but also on staying enrolled and hence the necessity to understand causes of dropping out. Until recently, research on dropping out of insurance as compared to enrolment has been less explored but there is a growing body of research on this front too. The dropout rates found in the literature are indeed very high. Four schemes studied by Mladovsky (2014) in Senegal indicated drop out ranging from 58 to 83 percent while the scheme in Sudan registered a 40 percent dropped out rate (Herberholz and Fakihammed, 2016). In Burkina Faso, Dong et al. (2009) reported dropout rates of above 45 percent against an enrolment of only 6 percent, while in Ghana, dropout rates increased to 35 percent in 2012 Atinga et al. (2015). The Ethiopia scheme also recorded dropout rates as high as 26.5 percent (Mebratie et al., 2015a). In India, only between 13 and 21 percent of households that enrolled in the first year of the scheme were members in the third year of the scheme, indicating dropout rates ranging from 79 to 87 percent (Panda et al., 2016).

From the few studies interrogating the drop out question so far, the major reasons for drop outs are related to: affordability of premiums (Herberholz and Fakihammed, 2016; Mebratie et al., 2015a; Atinga et al., 2015), limited scheme benefits (Atinga et al., 2015), perceived poor service quality in insurance providing facilities (Atinga et al., 2015; Dong et al., 2009; Mladovsky, 2014), poor understanding of insurance concepts and working (Herberholz and Fakihammed, 2016; Mebratie et al., 2015a), lower community participation and involvement

2.3 Empirical approach

The determinants of enrolment in CBHI schemes across developing countries are partly household related determinants, such as household income and wealth status, education levels of household heads and household sizes. Moreover, other non-household reasons such as distance from health facilities play a role (Dror et al., 2016). In addition, the amount of information available to households plays an important role to build trust and understanding, subsequent and enrolling in CBHI. Therefore, perceptions about CBHI are also important in the decision to enrol or not to (Jehu-Appiah et al., 2012). Several household variables are therefore included in the enrolment in CBHI model. In addition, spatial information such as distance and altitude of the households are collected and distance is included in the models.

The CBHI scheme of focus in this study has an additional enrolment condition; membership in a burial group. Burial groups across many developing countries, are central for community social support and are instrumental in the creation of health insurance networks (De Weerdt and Fafchamps, 2011; Dercon et al., 2004, 2006). At the introduction of CBHI in Uganda, burial groups were used as recruitment points because of existing social organisation and the ease of information flow (Carrin, 2003). Enrolment is therefore group-facilitated.[1] In order to capture the influence of burial group characteristics in our enrolment model, a couple of group variables are included. These are the size of the burial group, the number of burial groups operational in a village, a variable that captured whether households prefer to enrol as individual households or through groups and a variable that captured the influence of burial group leaders in decisions to enrol. Lastly, several village-level variables are also included in the models. To understand the determinants of enrolment and staying enrolled in CBHI, two models and employed. The first one is a binary logistic regression for household's insurance status. This basic model is given as:

$$\Pr\left(\mathrm{CBHI}\right) = 1_{\mathrm{ijk}} = \beta_0 + \beta_{1\mathrm{i}}\mathrm{X}_{1\mathrm{i}} + \beta_{2\mathrm{j}}\mathrm{X}_{2\mathrm{j}} + \beta_{3\mathrm{k}}\mathrm{X}_{3\mathrm{k}} + \epsilon_{\mathrm{ijk}}(2.1)$$

Where the probability that a household i is in insurance is dependent on X_{1i} - a vector of household specific variables, X_{2j} - a vector of spatial variables, X_{3k} - a vector of village level variables and an error term ϵ_i. This logistic model shows the determinants of household's insurance status reported by their odds ratios. The logistic model is tested for multicollinearity by estimating the Variance Information Factor (VIF), giving a mean VIF of 4.42 against a rule of thumb of 10. Moreover, the Hosmer-Lemeshow goodness of fit tests (Hosmer et al., 2013) are also undertaken to ensure correct model specification. The chi-square distribution under 10 percentiles with 8 degrees of freedom had a p-value of 0.251, indicating that the logistic model was reasonably well fit. Other tests of model classification also indicated that the model was correctly specified.

In addition to data on CBHI participation, information about the number of years of participation which gives a measure of continued participation in CBHI. To estimate the determinants of continued participation in CBHI, a ZINB model was employed. This model facilitates the estimation a dependent variable of non-negative count outcome which has a large over-dispersion tending to zeros. For instance, from the data, the outcome variable years of insurance, 56 percent of the observations do not participate in CBHI (zero years). The ZINB model, therefore, suits this data

[1] Enrolment is group-facilitated in that once a particular burial group has decided to enrol, it provides households with a platform to enrol. This is rather different from group-based enrolment since each household essentially pays its premiums rather than group-based premiums. There is no cross-subsidisation within groups. It is important to note that burial groups have also been utilised for the promotion of CBHI in Ethiopia (Asfaw and von Braun, 2005; Haile et al., 2014).

by accounting for excess zeros in the distribution and produces the best fit results for such excess zero distribution (Hu et al., 2011). Our basic model is then given as follows.

$$\text{Years in CBHI}_{ijk} = \beta_0 + \beta_{1i}\text{X}_{1i} + \beta_{2i}\text{X}_{2j} + \beta_{3i}\text{X}_{3k} + \epsilon_{ijk} \tag{2.2}$$

From this model, the number of years in CBHI can be determined by vectors for household, spatial, group and village variables, similar to the logistic regression above. The ZINB model performs two estimations. The first estimation, the inflation equation is a logistic estimation that models the probability that the outcome is observed as a zero. The second estimation then controls for this probability of observing a zero and estimates the probability of the outcome on the full range count data (Hilbe, 2014). In order to ascertain that the ZINB model is the appropriate model, a Vuong test which estimates the appropriateness of the model over the standard negative binomial model (Hu et al., 2011) is applied.

2.4 Results

2.4.1 Descriptive results

From a sample of 464 households, representative of the population in the three sub-counties, CBHI enrolment was of 44 percent. For those who were in insurance, the average number of years in insurance was 5.3 years. The surveyed children were on average 30 months old and respondent mothers were on average 30 years old. 55.4 percent of the mothers had delivered their last child in a health facility compared to the sub-regional average of 41.5 percent as established by Demographic and Health Survey (DHS) (UBOS and ICF International, 2012), though lower than the 2016 DHS finding of 69.7 percent (UBOS and ICF, 2018). About 30 percent of the households had at least one parent who had some secondary education. Households had food of at least four types in the previous day and had at least 1.5 meals per day. Households had on average 6 people and at least half of the households were of the Catholic faith. The surveyed households had an average 1.3 children aged less than 5 years. In addition, each household had at least 0.4 long lasting mosquito nets per household member. Slightly more than 55 percent of the survey mothers had delivered the surveyed child in a health facility. About 48 percent reported an interface with a traditional birth attendant (TBA). Interface with a TBA was assessed as a dummy for 1 if a mother had ever received advice from a TBA or if she has delivered one of her children with the help of a TBA, and 0 otherwise. About 47 percent of the respondent mothers had also received advice from a Village Health Team (VHT) member.

A composite variable for socioeconomic status of the households - a wealth index, was developed. The wealth index was developed from 41 individual variables representing household asset holding, water and sanitation, agriculture and livestock assets and housing quality. Using Principal Components Analysis (PCA) methodology (Filmer and Pritchett, 2001; Vyas and Kumaranayake, 2006), the variables were reduced into a single wealth index ranging from -1.7 to 8.4. Categorising this into five quintiles established that on average, households in the richest quintile were almost three times better off than those in the bottom poorest quintile.

A perception index based on 34 5-point Likert scale questions was developed following Jehu-Appiah et al. (2012). Using PCA, these questions were reduced to six perception dimensions, namely; premiums, convenience of the scheme, financial protection, and management of the scheme, quality of care, and health beliefs, and one overall index. To measure knowledge about CBHI, respondents were asked whether they knew the amount of premiums paid per head in their households. About 53 percent knew the actual premiums for each individual in the household.

As enrolment in CBHI was based on membership in a burial group, some information on burial groups was collected as well. On average, burial groups had about 72 households and each village had about 2 burial groups enrolled in insurance. 69 percent of the respondents had at least one neighbour participating in CBHI. Table 7 provides more of these descriptive findings.

2.4.2 Empirical results

2.4.2.1 Determinants of enrolment in CBHI.

Table 8 below, presents results from the two regressions models. Model 1 presents results for a logistic regression for the determinants of enrolment in CBHI with odds ratios and 95 percent robust confidence intervals reported. Starting with the factors that inhibit enrolment in CBHI, it is found that children's age had a negative association with a household's enrolment status. An increase in an under-five child's age by one month was associated with a reduction in the likelihood of enrolment by 4.4 percent (OR 0.956; 95% CI 0.932 - 0.980). Larger households were associated with reduced odds of enrolment by 24 percent (OR 0.760; 95% CI 0.616 - 0.937). Households in which at least one parent had attended some secondary education were also less likely to enrol in CBHI. The likelihood of enrolling was 58.9 percent lower for these households (OR 0.411; 95% CI 0.155 - 1.092). It is further found that households in burial groups with a relatively large number of households were less likely to enrol in CBHI with odds of enrolling reducing by 2.8 percent (OR 0.972; 95% CI 0.953 - 0.991)

Turning to factors that facilitated enrolment in CBHI, controlling for household, group and village variables, we find that households with older mothers were likely more likely to enrol with odds of enrolment higher by 7.1 percent (OR 1.071; 95% CI 0.998 - 1.148). Belonging to the Catholic faith was associated with increasing a household's odds of enrolling in CBHI by over three times (OR 3.144; 95% CI 1.363 - 7.248). There was a significant influence of household's socioeconomic status. Compared with households in the poorest quintile, households in the upper quintiles

Table 2.1: Descriptive results

Variables	Man	Min	Max	S
CBHI participation	0.438	0	1	0.497
Years in CBHI	5.345	1	20	3.561
Child's age	30.202	5.550	60.580	15.152
Mother's age	30.204	14.010	56.540	7.164
Birthweight	3.185	2.000	5.600	0.528
Number of under-5	1.332	1	3	0.511
Catholic	0.504	0	1	0.501
Parental secondary education	0.304	0	1	0.460
Average daily meals (7 day recall)	1.494	1	3	0.588
HDDS	4.080	0	8	1.280
Wealth index quintile 1	−1.280	−1.754	−0.999	0.193
Wealth index quintile 2	−0.784	−0.997	−0.565	0.123
Wealth index quintile 3	−0.286	−0.564	−0.052	0.153
Wealth index quintile 4	0.315	−0.051	0.766	0.254
Wealth index quintile 5	2.212	0.767	8.365	1.435
LLIN per capita	0.436	0	3	0.281
Health facility delivery	0.554	0	1	0.498
Neighbour in CBHI	0.692	0	1	0.462
Access to information	-2.20×10^{-09}	−2.631	4.472	1.289
Perception index	-1.24×10^{-09}	−3.331	3.599	1.741
Interface with TBA	0.476	0	1	0.500
Interface with VHT	0.466	0	1	0.499
Husband's employment - casual	0.356	0	1	0.479
Mother's employment - casual	0.101	0	1	0.302
Know premium	0.528	0	1	0.500
Waiting time in minutes	88.621	5	540	108.851
Size of burial group	71.366	18	200	26.054
Number of groups household belongs to	1.829	0	5.000	1.003
Village group per capita	0.032	0.004	0.160	0.032
Village had a primary school	0.528	0	1	0.500
Village has a health centre	0.401	0	1	0.491
Main economic activity - trading	0.366	0	1	0.482
Main economic activity - banana cultivation	0.261	0	1	0.440
Distance to neared health facility (kms)	4.001	0	11.5	2.919
N		464		

[1]Years in insurance (insurance intensity) only for 203 households who were in insurance (43.8 percent). There are 94, 92 97, 95 and 86 observations for wealth quintiles 1 to 5 respectively.

were more likely to enrol in CBHI. Households in the third quintile were 3.7 times more likely to enrol compared to the bottom poorest quintile (OR 3.773; 95% CI 1.141 - 12.406). Households in the fourth quintile were 3.5 times more likely to enrol (OR 3.532; 95% CI 1.058 - 11.790) compared to the lowest quintile. At the same time, households in the richest quintile were 4.5 times more likely to enrol (OR 4.482; 95% CI 1.159 - 17.334). However, we find that households in the poorer second quintile were worse off than the poorest. Their odds of enrolment were close to 80 percentage points lower (OR 0.218; 95% CI 0.073 - 0.652). Information and connectivity, measured as a composite indicator of listening to radio, reading newspapers and owning a mobile phone with mobile banking facilities, engagement in lending and borrowing and level of group participation, was found to increase the odds of enrolment by 65 percent (OR 1.648; 95% CI 1.104 - 2.460).

Perceptions about CBHI were important for enrolment decisions as well. Households with more positive perceptions were close to 1.6 times (OR 1.561; 95% CI 1.128 - 2.161) more likely to enrol compared to those with negative perceptions. Community health workers, also referred to as VHTs also do have a positive influence on household's decisions to enrol. It was found that households that had received advice were over 2.2 times (OR 2.235; 95% CI 1.015 - 4.922) more likely to enrol in CBHI. Two more factors were important for enrolment in CBHI. The amount of knowledge and information households had about the scheme and employment status of the household heads. Households in which the husbands were employed in casual work were more than 5 times more likely to enrol in CBHI (OR 5.321; 95% CI 1.801 - 15.720). Knowing CBHI premiums, a proxy of knowledge about the scheme was associated with increasing the odds of enrolment by over 32 times more likely to enrol (OR 31.955; 95% CI 13.197 - 77.380) compared to households in which the respondent did not know the premiums. In other words, households that were not participating knew very little about CBHI.

2.4.2.2 Determinants of staying in CBHI

The interest in analysing the determinants of continued participation in CBHI is because staying in CBHI is equally important especially in view of high dropout recorded in other CBHI schemes across developing countries. The outcome of this ZINB model is a count of the number of years of continued participation in CBHI. Results are shown in Model 2 of Table 8 with incident rate ratios and 95 percent confidence intervals. After controlling for the over-dispersion in the number of years in CBHI, it is found that most of the factors associated with enrolling in CBHI were also associated with staying in CBHI. Households with older mothers were more likely to remain enrolled for an extra year with odds improved by 4.2 percent (IRR 1.042; 95% CI 1.018 - 1.067) higher than households with relatively younger mothers

Households of the Catholic faith were almost 1.6 times more likely to stay enrolled in CBHI (IRR. 1.573; 95% CI 1.204 - 2.054). Strong associations were found regarding the use of long-lasting insecticide mosquito nets (LLIN) and delivering in a health facility. Households which had a higher LLIN per capita were 2.8 times (IRR 2.805;

Table 2.2: Determinants of enrolment and staying in CBHI

	Model 1: Enrolling in CBHI			Model 2: Staying in CBHI		
VARIABLES	Odds ratio	SE	95% CI	IRR	SE	95% CI
Child's age	0.956***	(0.012)	0.932 - 0.980	1.001	(0.004)	0.993 - 1.010
Mother's age	1.071*	(0.038)	0.998 - 1.148	1.042***	(0.013)	1.018 - 1.067
Birthweight	0.653	(0.283)	0.280 - 1.526	1.038	(0.122)	0.824 - 1.308
Household size	0.760**	(0.081)	0.616 - 0.937	0.987	(0.040)	0.911 - 1.069
Catholic	3.144***	(1.340)	1.364 - 7.248	1.573***	(0.214)	1.205 - 2.054
Some secondary education	0.411*	(0.205)	0.155 - 1.092	0.932	(0.145)	0.686 - 1.265
Food adequate	0.881	(0.371)	0.386 - 2.011	0.830	(0.121)	0.623 - 1.106
HDDS	0.963	(0.154)	0.703 - 1.318	0.953	(0.051)	0.858 - 1.058
LLIN per capita	4.654	(5.711)	0.420 - 51.572	2.805**	(1.187)	1.224 - 6.430
Hospital delivery	1.707	(1.193)	0.434 - 6.719	1.565*	(0.385)	0.967 - 2.533
Hospital delivery *LLIN per capita	0.181	(0.249)	0.012 - 2.694	0.343**	(0.172)	0.128 - 0.918
Wealth index (base: quintile 1)			-			-
Quintile 2	0.218***	(0.122)	0.073 - 0.652	0.920	(0.196)	0.606 - 1.397
Quintile 3	3.763**	(2.290)	1.141 - 12.406	1.544**	(0.313)	1.037 - 2.298
Quintile 4	3.532**	(2.172)	1.058 - 11.790	1.732***	(0.351)	1.164 - 2.577
Quintile 5	4.482**	(3.093)	1.159 - 17.334	2.901***	(0.771)	1.723 - 4.883
Neighbour in CBHI	1.659	(0.991)	0.515 - 5.350	1.661**	(0.359)	1.088 - 2.536
Access to information	1.648**	(0.337)	1.104 - 2.460	1.227***	(0.068)	1.101 - 1.368
Perception index	1.561***	(0.259)	1.128 - 2.161	1.040	(0.049)	0.949 - 1.140
Access to info*perception index	0.945	(0.118)	0.739 - 1.207	0.981	(0.029)	0.925 - 1.040
Know or used a TBA	0.474	(0.222)	0.189 - 1.186	0.822	(0.123)	0.612 - 1.103
Received advice from VHT	2.235**	(0.900)	1.015 - 4.922	1.291*	(0.172)	0.995 - 1.676
Husband's employment - casual	5.321***	(2.941)	1.801 - 15.720	1.241	(0.178)	0.937 - 1.644
Mother's employment - casual	0.557	(0.444)	0.117 - 2.653	0.757	(0.188)	0.465 - 1.231
Know premium	31.955***	(14.419)	13.197 - 77.380	3.670***	(0.677)	2.557 - 5.268
Waiting time	1.002	(0.002)	0.999 - 1.006	1.000	(0.001)	0.999 - 1.001
Burial group size	0.972***	(0.010)	0.953 - 0.991	1.007*	(0.004)	0.999 - 1.014
Number of burial groups in village	1.531***	(0.188)	1.203 - 1.947	1.248***	(0.065)	1.127 - 1.382
Prefer enrolment w/t burial groups			-			-
(base: strongly disagree)			-			-
Disagree	6.722***	(4.132)	2.015 - 22.424	1.824***	(0.349)	1.254 - 2.655
Neutral	1.131	(0.844)	0.262 - 4.881	1.047	(0.267)	0.635 - 1.727
Agree	3.826**	(2.283)	1.188 - 12.322	1.756***	(0.350)	1.188 - 2.596
Fully agree	0.538	(0.421)	0.116 - 2.492	0.911	(0.158)	0.649 - 1.279
Leaders influence	1.264*	(0.175)	0.964 - 1.658	1.117**	(0.054)	1.016 - 1.227
Village has a primary school	0.258**	(0.150)	0.082 - 0.808	0.703*	(0.147)	0.467 - 1.058
Village has health centre	0.590	(0.318)	0.205 - 1.696	1.220	(0.309)	0.743 - 2.004
Village economy - trading	0.351*	(0.217)	0.105 - 1.178	0.522***	(0.126)	0.325 - 0.840
Village economy - banana	0.101***	(0.073)	0.024 - 0.419	0.666*	(0.141)	0.440 - 1.007
Distance to nearest health centre	0.956	(0.130)	0.732 - 1.248	0.960	(0.047)	0.872 - 1.057
Constant	0.300	(0.712)	0.003 - 31.390	0.019***	(0.015)	0.004 - 0.089
Mean VIF	6.39		-			-
Link test (hat squared)	-0.053	(0.035)	-			-
Hosmer-Lemeshow GOF P-value	0.3054		-			-
Pseudo R-squared	0.6536		-			-
Vuong test			-	4.26	(0.000)	-
Observations		452			452	

Robust exponential standard errors and exponential standard errors in parentheses for Model 1 and Model 2 respectively. Significance level corresponding to *** p<0.01, ** p<0.05, * p<0.1

95% CI 1.224 - 6.430) more likely to renew their participation in CBHI for an additional year. Likewise, delivering in a health facility it was established that households in which a mother delivered from a health facility were 1.5 times (IRR 1.565; 95% CI 0.967 - 2.533) more likely to renew their participation in CBHI. Just like enrolling in CBHI, there was a strong association between socioeconomic status of the household and continued participation when households in the lowest quintile were compared to those in the upper quintiles and the lowest quintile. Households in the third quintile were 1.5 more likely to remain in CBHI for an extra year (IRR 1.1544; 95% CI 1.037 - 2.298) while those in the fourth quintile were over 1.7 times more likely to stay in CBHI (IRR 1.732; 95% CI 1.164 - 2.577). Moreover, the richest households in the richest fifth quintile were almost three times as likely to stay in CBHI (IRR 2.901; 95% CI 1.723 - 4.883) compared to the poorest quintile.

Significant neighbourhood effects were also found. Households which had at least one neighbour participating in CBHI were 1.6 times more likely to continue participating in CBHI (IRR 1.661; 95% CI 1.088 - 2.536). In addition to neighbourhood, effects were information effects. Households with more access to information were 23 percent (IRR 1.227; 95% CI 1.101 - 1.368) more likely to continue participating compared to households with less access to information. As with enrolling in CBHI, we find a significant effect of VHT interface. Households which had received health-related information from a VHT were found to have 30 percent more odds of renewing membership in CBHI by an additional year (IRR 1.291; 95% CI 0.995 - 1.676). Moreover, households whose respondent could correctly tell the premiums required of her household to enrol were 3.7 times more likely to renew membership by an additional year (IRR 3.670; 95% CI 2.557 - 5.268) compared to households which did not know the premiums.

There were positive associations regarding the number of burial groups participating in CBHI in the village and the overall size of a burial group in which a household belonged. An increase by 1 in the number burial groups participating in CBHI in the village was associated with increasing the likelihood of renewing membership by 25 percent (IRR 1.248; 95% CI 1.127 - 1.382) while an increase by 1 in the number of households in a burial group was associated with increasing the likelihood of renewing membership by 0.7 percentage points. Additional group variables such as leadership influence and preference to enrol as individual households as opposed to the requirement to belong in a burial group were also included in the model. It was found that households which felt community leaders influenced them regarding participation in groups had a 26 percent higher likelihood of enrolling (IRR 1.264; 95% CI 0.964 - 1.658) and 12 percent higher likelihood of renewing membership (IRR 1.117; 95% OR 1.016 - 1.227). Apart from the village controls in the model, one variable that was associated with reducing the odds of renewing membership, an interaction between LLIN per capita and delivering in a health facility. Households that had a higher LLIN per capita and also had the mother deliver in a hospital were 66.7 percentage points (IRR 0.343; 95% CI 0.128 - 0.918) less likely to renew membership in CBHI.

2.4.2.3 Effect of perceptions on enrolment and staying insured.

The analysis also followed Jehu-Appiah et al. (2012) on quantitatively assessing the influence of household perceptions on decisions to enrol and remain in insurance. To study the association of perceptions on enrolment, a single composite perception index as well disaggregated indicators of six perceptions were regressed on CBHI status. Table 9 provides logistic regression results of the association between the overall perception index and disaggregated perceptions and decision to enrol in CBHI. It was that in general, positive perceptions were associated with the decision to enrol by increasing the odds by 55 percent (OR 1.551; 95% CI 1.379 - 1.744). Moreover, the interest was also to identify which perceptions were more influential in decisions to enrol. Due to the multicollinearity in the perceptions, we include only five of the six perceptions in the model.

Table 2.3: Influence of perceptions on enrolment in CBHI

	Model 1				Model 2			
	Odds ratio	SE	95%CI		Osratio	SE	95% CI	
Overall perception index	1.551***	(0.093)	1.379 -	1.744			-	
Management of the scheme			-		1.187*	(0.112)	0.986 -	1.429
Quality of care			-		1.067	(0.094)	0.898 -	1.267
Health beliefs			-		0.978	(0.094)	0.810 -	1.181
Financial protection			-		0.959	(0.055)	0.856 -	1.074
Premiums			-		0.616***	(0.061)	0.507 -	0.748
Constant	0.755***	(0.076)	0.620 -	0.919	0.746***	(0.075)	0.613 -	0.908
N		464				464		

Robust exponential standard errors in parentheses.
Significance level corresponding to *** p<0.01, ** p<0.05, * p<0.1

The results show that of the five perceptions included in the model, only one of them, perceptions on the management of the scheme, had a significant association with enrolment. Positive perceptions about scheme management were associated with increasing the odds of enrolment by close to 19 percent (OR 1.187; 95% CI 0.986 - 1.429). Conversely, perceptions about premiums paid for insurance were associated with reducing the odds of enrolment by up to 38.4 percent (OR 0.616; 95% CI 0.507 - 0.748). In other words, when households believe that the premiums are high or unaffordable, they are less likely to enrol in CBHI. Significant effects regarding perceptions on financial protection or quality of care are not observed. These results indicate that while some individual perceptions are important, overall perception index was probably more important than individual perceptions and so encouraging households to enrol could focus more on improving average perceptions as opposed to targeted interventions on individual areas of concern.

This study was also interested in understanding which perceptions were important for remaining in CBHI. A ZINB regression was therefore executed with the number of years of in CBHI as the outcome. The results shown in Table 10 below generally reveal that perceptions are not significantly associated with a household's renewing decisions. Indeed even the general model in Table 8 above, no significant effect was observed. However, it is observed once again that there was a negative association regarding perceptions on premiums. Though mildly significant, it was found that households which viewed premiums as high, were 8.9 percentage points less likely to renew their membership in CBHI (IRR 0.911; 95% CI 0.821 - 1.010).

Table 2.4: Influence of perceptions on staying enrolled in CBHI

	Model 1			Model 2		
	IRR	SE	95%CI	IRR	SE	95% CI
Overall perception index	1.014	(0.030)	0.957 - 1.075			-
Management of the scheme			-	0.991	(0.041)	0.913 - 1.075
Quality of care			-	0.970	(0.043)	0.889 - 1.057
Health beliefs			-	1.032	(0.053)	0.932 - 1.141
Financial protection			-	1.020	(0.030)	0.963 - 1.080
Premiums			-	0.911*	(0.048)	0.821 - 1.010
Constant	5.022***	(0.268)	4.524 - 5.576	4.890***	(0.274)	4.380 - 5.459
N		464			464	

Robust exponential standard errors in parentheses.
Significance level corresponding to *** $p<0.01$, ** $p<0.05$, * $p<0.1$

2.5 Discussion and conclusions

This study is the first known attempt to qualitatively study the determinants and continued participation in Ugandan CBHI schemes, adding on previous qualitative studies (Basaza et al., 2007, 2008, 2010; Twikirize and O'Brien, 2012). The results revealed in this study can be understood better when one puts into perspective the existence of burial societies as informal insurance systems and CBHI as the formalisation of informal health insurance in the context of rural Uganda (Cecchi et al., 2016).

To give a brief overview of burial groups in this case study, all households in the sample and the community, in general, belong to a burial group, in agreement with previous work in this region (Katabarwa et al., 1999; Musau, 1999). These burial groups are exogenously formed in such a way that households have limited choice on which group to belong to, but rather follow patrilineal lineages (Katabarwa et al., 2000a). The existence of burial groups and their role in health insurance is not limited to south-western Uganda. In fact, burial groups have been found in Ethiopia and Tanzania, where they also play a succinct role in faciliting informal insurance, including health insurance (Asfaw, 2003; Dercon et al., 2006; Hailemariam, 2003).

One important thing is that burial groups provide a platform of formalisation of health insurance in rural south-western Uganda but CBHI is not implemented as group insurance in a sense that individuals in a burial group do not pool resources as a group or insure on one group policy. However, several things matter, on decisions to enrol or continue participating in CBHI, at the group level. As has been stated elsewhere, especially in behavioural economics and psychology, group sizes matter in the provision of socially oriented goods, in such a way that large groups have higher levels of altruism and social support (Genicot and Ray, 2003; Hindriks and Pancs, 2002; Isaac et al., 1994; Schumacher et al., 2017). However, there might be social costs of management and acquisition of information making small groups more effective (Scharf, 2014). The variable of burial group size was therefore included in the models as an important group characteristic. A negative association was found between group size and the enrolment but a positive association was found regarding renewing CBHI membership or continued participation. These signs are in line with the theory, that due to higher per capita utility from larger groups (Genicot and Ray, 2003), members are less likely to seek additional insurance when they have large informal insurance to rely on. However, the main fabric of burial groups is supporting others out of both egalitarianism and expected behaviour and conduct of reciprocity. It, therefore, appears that when a household enrols for CBHI, it is more likely to renew membership and not drop out due to additional support from other group members.

One of the things that could make burial-group based CBHI special is stronger social support, and therefore inclusion of the poor, and the elderly, and the avoidance of adverse selection (Parmar et al., 2012). Recent literature has focused on the understanding exclusion of vulnerable groups from CBHI programmes across developing countries (Mladovsky and Ndiaye, 2015; Parmar et al., 2014; Williams et al., 2017). Since this study's survey was not particularly designed to respond to the exclusion question in its multiple dimensions, it is only limited to analysing socioeconomic exclusion based on wealth quintiles. From the understanding of social support systems within burial groups, it would be expected that the poor and rich across all quintile would have no statistically significant differences regarding the likelihood of enrolment and/or staying in CBHI. However, it was established that substantial differences, which can be interpreted as exclusion of the poorest households existed. Households from the top three quintiles were 3.5 to 5 times more likely to enrol in CBHI and 1.5 to 3 times more likely to renew their membership, compared to poorest households. It, therefore, seems that protection from dropping out is only possible to the already CBHI-participating households and barriers to enrolment for the poorest household exist.

The results regarding exclusion of the poorest are important for the government of Uganda which is in the process of establishing a national health insurance programme, expected to include existing CBHI schemes. For the future of CBHI in particular and the national health insurance programme in general, this study recommends that the government and other stakeholders devise mechanisms of enabling equitable participation of the poor. These might include premium waivers for the poor and progressive premiums for the better-off households as has been recently introduced in Rwanda (Kalisa et al., 2015). Another possible avenue of including the vulnerable population is taking CBHI within the broader spectrum of social protection programmes for the poor. In this case, social protection instruments such as cash transfers are can supplement other social support systems such as CBHI, in agreement with recent studies that support combining CBHI with other social protection programmes for both health and socioeconomic outcomes (Shigute et al., 2017a,b).

The other issue which this research finds important relates to social connectivity through access to information. The measure of access to information used combines several variables including engagement in lending and borrowing, having a connection to a village leader, listening to radio, television and reading newspapers. This composite variable can also be seen as a proxy of broader social capital held by a household (Woolcock and Narayan, 2000). The relationship between social capital and CBHI has been studied and findings strongly suggest social capital is a significant determining factor of enrolment in health insurance programmes in developing countries (Cecchi et al., 2016; Donfouet and Mahieu, 2012; Fenenga et al., 2015; Mladovsky and Mossialos, 2008; Mladovsky, 2014). The finding on access to information is in agreement with previous findings that social capital and social connectivity were important for both initial enrolment in CBHI and continued participation.

Another aspect of social capital and social networking that was found is in relation to neighbourhood effects regarding continued participation in CBHI. Having a neighbour participating in CBHI was found to have increased the chances on an enrolled household renew its membership (in other words limiting drop out). This finding is again related to another dimension of social capital, the concept of social learning. Studies from public health and development economics have shown that households learn from each other to adopt new technologies and innovations.[2] For health insurance in particular, Liu et al. (2014) found that in rural China, a 10 percentage point increase in enrolment rates in a village increased a household's probability of insurance take-up by 5 percentage points, a finding that was associated to social learning among village members. The evidence in this study is consistent with these previous studies; that adopters learn from their peer early adopters and that the wider the peer network the higher the probability of adoption. From a policy perspective, it is important for developing programs to leverage of existing networks of social capital such as burial groups. In essence, these form the bedrock of community social actions that are essential for diffusion of information and learning (Katabarwa et al., 2010a,b, 2000a). Nonetheless, the introduction of interventions such as health insurance in villages needs to be careful of possible destabilisation of such social systems (Cecchi et al., 2016) in order to find mutually reinforcing strategies that strengthen such systems as well as achieve uptake.

This study finds that one main issue that reduced the likelihood of participating in CBHI was education levels, portrayed by either parental education or if a village had a school. In both cases, the likelihood of CBHI participation was lower. Previous studies find that parental

[2]For instance in adopting new agricultural technologies (Conley and Udry, 2001, 2010; Foster and Rosenzweig, 2010), adoption in public health interventions (Kohler et al., 2001, 2007; Oster and Thornton, 2012; Shakya et al., 2014, 2015)

CHAPTER

THREE

IMPACT OF COMMUNITY-BASED HEALTH INSURANCE ON CHILD HEALTH OUTCOMES: EVIDENCE ON STUNTING.

3.1 Introduction

Community-Based Health Insurance (CBHI) schemes are a particular form of health insurance systems emanating from community social support systems (Criel et al., 2004), often working in the rural informal sector, and operating without profit motivations (Bennett et al., 1998). The schemes evolved in the 1980s especially in resource-poor developing countries where tax-funded and other health insurance platforms were non-existent (Carrin et al., 2005; Ekman, 2004); and have over the last few decades evolved as essential buffers for financial protection and enabling health services access, especially in poor rural communities. They currently form essential building blocks to achieving universal health coverage in developing countries (Jacobs et al., 2008; Titelman et al., 2015; Wang and Pielemeier, 2012) and have been adopted across many countries with varying forms and levels of government involvement.

Studies on community-based health insurance have proliferated health economics and health policy literature, often discussing issues on enrolment and drop out (Atinga et al., 2015; De Allegri et al., 2006; Dror et al., 2016; Mebratie et al., 2015a; Panda et al., 2014), facilitating access to health services (Jutting, 2004; Mebratie et al., 2013; Smith and Sulzbach, 2008; Sood and Wagner, 2016), financial protection (Nguyen et al., 2011; Nguyen, 2012; Sepehri, 2014; Sepehri et al., 2011), and wider welfare as well as economy-wide impacts on risk-coping and managing shocks (Asfaw and von Braun, 2004a,b; Landmann and Frölich, 2015; Yilma et al., 2014, 2015). However, research evidence remains thin on the impact of community health insurance on health outcomes such as disease reduction and improved health indicators in children and mothers, or improved adoption of preventive health behaviours. Several systematic reviews that combine hundreds of published research (Adebayo et al., 2015; Dror et al., 2016; Ekman, 2004; Mebratie et al., 2013; Reshmi et al., 2016; Spaan et al., 2012) did not report any evidence of effects on health outcomes. In only one of the recent systematic reviews (Acharya et al., 2013) are health outcomes reported and even then in only six of nineteen papers in the review. The authors found this surprising, that research has paid limited attention to health outcome effects of insurance. The basic question asked by Dror (2014) about the impact of health insurance-induced utilisation of care on health outcomes of target populations, therefore, remains largely unanswered. This constitutes a real research gap which this chapter intends to address. In an attempt to contribute to the narrowing this research gap, this chapter focuses on the effect of CBHI on child nutritional indicators, especially the long-term measure of child stunting.

This study adds to an emerging body of literature on health insurance and health outcomes. For instance, Hendriks et al. (2014, 2016) studied the short and medium term effect of CBHI on systolic and diastolic blood pressure in Nigeria while Sood and Wagner (2016) studied the effects on post-operative recovery in India. In terms of child nutrition-related health outcomes, two studies looked at CBHI's effect on stunting and wasting. These are Lu et al. (2016) who study the effect on stunting for children between 6 and 24 months in Rwanda and Quimbo et al. (2011) who study the effect on wasting in the Philippines. There are a couple of differences regarding the two child health studies and therefore new contributions that this chapter makes. Two issues are in relation to Lu et al. (2016) study in Rwanda. Whilst Rwanda provides one of the best examples of CBHI in scale-up, it can hardly be considered as voluntary health insurance, and therefore diverges from one of the key precepts of CBHI - voluntary enrolment. Since 2007, CBHI in Rwanda has been compulsory (Nyandekwe et al., 2014) and the health insurance law was further revised in 2015 (Government of Rwanda, 2016). CBHI in Uganda, on the other hand, is completely voluntary and outside the government public health sector services. Secondly, while Lu et al. (2016) had access to rich country level DHS data, which they were able to link with health facilities clinical data, but they chose a narrow 6-24 months children and hence their results cannot be interpreted in the context of all under-5 children. The Philippines study (Quimbo et al., 2011) uses experimental data from a health facility-administered intervention. The drawback here is that in many developing countries like Uganda, clinically recorded data represents only a section of the population. For instance, only 58 percent of mothers delivered in health facilities in Uganda (UBOS and ICF International, 2012). To improve on these two papers, the data used in this chapter is from a household survey that was designed to capture all households in the community; that is, those that had clinical information and those that had less interface with health facilities.

To account for possible endogeneity between health insurance and child health outcomes (Levy and Meltzer, 2008), a novel Instrumental Variable (IV) approach, the Two-Stage Residual Inclusion (2SRI) method (also referred to as the control function approach) (Terza et al., 2008; Wooldridge, 2015) was employed. Following the framework set out by Terza (2017a), this method facilitates modelling not only the effect on CBHI status but also the effect of a number of years of participation in CBHI as CBHI intensity.

The main contribution to health economics literature in this chapter, is the demonstration that CBHI can influence health beyond its primary goals of resource mobilisation for health systems and financial protection for households in developing countries. The results indicate that the probability of child stunting reduced by 5.7 percentage points for each year a household was enrolled in CBHI. Predictive marginal effects reflect that contrasted with children in households not enrolled in CBHI whose probability of stunting was 51.5 percent, probability of stunting for children in households in CBHI reduces from 49.2 percent with CBHI membership for only one year to 37.6 percent if they remained members for 5 years. By asking and answering these questions, some extra evidence that health of children improves when their households enrol in CBHI is provided.

The rest of this chapter is organised as follows. Section 3.2 briefly discusses the stunting problem in developing countries and Uganda in particular. Section 3.3 reviews literature on CBHI and other voluntary health insurance programs and health outcomes. Section 3.4 gives the empirical strategy of the paper by briefly discussing the stunting problem in Uganda and then elaborating on the IV identification strategy used. Section 3.5 provides the detailed results and section 3.6 discusses them and concludes the chapter.

3.1.1 The stunting problem

Stunting also referred to as low height for age is assessed using the World Health Organisation growth monitoring standards as prevalent when the height-for-age Z-score has a standard deviation of -2 or less of the age-specific healthy children (Duggan, 2010). Low height for age affects an estimated 165 - 170 million children in the world and affects developing countries disproportionately (Prendergast and Humphrey, 2014; Stevens et al., 2012). The effects are not only detrimental to a child's young life but also sustain into adulthood, affecting educational, health, employment and cognitive abilities later in life (Case and Paxson, 2010; Dewey and Begum, 2011; Glewwe et al., 2001; Glewwe and Miguel, 2008; Vogl, 2014).

Uganda, in particular, grapples with the stunting problem, with over 33 percent all the children in the country stunted (UBOS and ICF International, 2012). Using the 2014 census (17.7 percent of 34.8 million under 5 years), this stunting prevalence would translate into 1.8 million stunted children.[1] It is not simply high but also increasing in some regions such as Central 2 and Western (UBOS and ICF International, 2012). The south-western region, where this research took place had the third highest stunting of 41.7 percent in 2011. Nutrition practitioners warn that if the current status of stunting is not improved, stunting could lead to loss of more than half a million lives between 2013 and 2025 (Namugumya et al., 2014). Such a tragedy would disproportionately affect rural households.

Table 3.1: Child stunting in Uganda(% of U-5 children)

Region	2006	2011
Kampala	22.2	13.5
Central 1	39.2	32.5
Central 2	29.8	36.1
East Central	38.3	33.5
Eastern	36.2	25.3
Northern	40.0	24.7
West Nile	37.7	37.8
Western	37.6	43.9
South Western	49.6	41.7
Karamoja	53.6	45.0
Average	**38.1**	**33.4**

Source: Demographic and Health Surveys, 2006 and 2011.

[1]Results from the 2016 DHS(UBOS and ICF, 2018) indicate stunting prevalence of 28.9 percent and 30.8 percent for Kigezi region where this study area is located. However, the due a change in regional reclassification, we have not included those results here.

3.2 Health Insurance and Health Outcomes in Developing Countries: State of the Art

Evidence regarding CBHI effects on health outcomes in developing countries is still scarce and very recent. For instance, a compilation of research studies about the impacts of health insurance provided only four studies directly dealing with health outcomes, against 31 and 27 on the utilisation of care and financial protection respectively (Morsink, 2012). It is important to note that even in this small body of research, the evidence is inconclusive about whether health insurance improved health outcomes. Some studies find positive health effects of insurance while others find negative effects. This gives further justification that more research in this area is required.

Fink et al. (2013) analysed the impact of the Nouna scheme in Burkina Faso on mortality and found that insurance appeared to have increased overall mortality rather than reduce it. They find that overall population mortality increased by more than 20 percent in villages with CBHI when compared with the overall average, especially in the over 65 age group. Their study also did not find a significant effect on under-5 child mortality. Conversely, Sood et al. (2014) studying the effect of the Vajpayee Arogyashree Scheme (VAS) on mortality in India, found positive results from their large sample of over 60,000 households. They found a 0.58 percentage point difference in mortality from covered conditions in insurance villages compared with non-insurance villages, which represented a 64 percent risk reduction. They further looked at the age-specific mortality caused by insurance-covered conditions and found that in the insured households 52 percent of the mortality was in the 60 years population compared to 76 percent in the same age classification for the non-insured households. This implied that overall health services improved in villages with insured households.

Sood and Wagner (2016) also studied the effect of VAS insurance on post-operative health and recovery and found that insured people reported more positive improvements after an operation in all the six categories of self-assessed health (self-care, usual activities, walking ability, pain, anxiety and overall health) and statistical significance in three categories, that is; walking ability, pain, and anxiety. Insured people were also 9.4 percentage points less likely to report an infection after their stay in a hospital, 16.5 percentage points less likely to be re-hospitalized and 5 percentage points more likely to seek treatment if it was needed. In Nigeria, two chronological studies assessed the impact of health insurance on hypertension over the short and medium term. In the first study, Hendriks et al. (2014) assessed health outcomes using changes in blood pressure in two regions in Nigeria. Using the difference in differences method, they found that systolic blood pressure reduced by 5.2 mm Hg more in treatment villages compared to the control villages while diastolic blood pressure reduced twice as much. Sustained effects measured in the medium term, after 5 years indicated that systolic blood pressure maintained a greater reduction of 4.97 mm Hg in treatment villages (Hendriks et al., 2016).

Focusing on health outcomes specifically for children, though the research is scarce, a handful of papers try to unearth impacts and the general consensus is positive. Two papers evaluating the national insurance scheme in Rwanda found some positive effects on early childhood stunting and infant mortality. Binagwaho et al. (2012) used two rounds of the Rwanda Integrated Households and Living Standards survey and found height-for-age z-scores (measuring stunting) gains of 0.42cm for children between 6 and 24 months. They further found that the risk of infant death was lower by up to 14 percentage points compared to uninsured households. A more recent paper on Rwanda also reported that the probability of stunting for children enrolled in insurance was 14 percentage points lower than those not enrolled Lu et al. (2016). In the Philippines, Quimbo et al. (2011) found that voluntary insurance had a causal effect of up to 12 percentage points reduction in wasting. In Burkina Faso, analysis based on data from over 33,000 children found that the risk of mortality was 46 percent lower for insured children compared with their uninsured counterparts (Schoeps et al., 2015).

Overall, evidence on whether CBHI or other private insurance programs for the poor improve health outcomes is still scanty and only emerging. This is especially so concerning child health outcomes to which this chapter contributes to. Whilst the importance of other health outcomes in the broader health spectrum is not diminished, child health outcomes such as nutrition improvement, remain a priority for developing countries and learning how insurance could nudge improvements in this area should remain a priority in both academics and policy-making. For East Africa, a region where CBHI policymaking has gained momentum (Basaza et al., 2013; Abuya et al., 2015) and to almost universal coverage in Rwanda (Lu et al., 2012), such evidence is required to make further informed policies as well as demonstrate impact. Using this case study from rural south-western Uganda, it is hoped that some contribution to literature will be made in this regard.

3.3 The empirical strategy

3.3.1 Treatment and control variables

Treatment: The treatment exposure, CBHI status was measured in two ways; first as a dummy of CBHI membership and then as a count measure of the number of years a household had participated. The method of analysis chosen allows for the combination of these two exposure measures. Because stunting is a long-term health outcome, the chosen estimation method also gives a more intuition in that the intensity of treatment (years in CBHI) is incorporated in the interpretation.

Other Covariates: Other covariates can be categorised into three categories, namely; child specific covariates, household covariates and village level covariates.

Child-specific covariates: The child-specific covariates in the model include the age of the child in months and its quadratic term. A child gender dummy that specifies 1 if male and 0 otherwise was included. Birth weight is an important determinant of child growth (Wilcox, 2001) and has long-term effects on education and labour market participation in adulthood (Behrman et al., 2004; Chatterji et al., 2014; Xie et al., 2016). In the data collected, birthweight was recorded for only 55.4 sample of the sample - children who were born in health facilities. A multiple imputation procedure using a linear regression (Rubin, 1987; Schenker and Taylor, 1996) was therefore applied to impute the birthweight of the remaining 44.6 percent of the sample.[2] A dummy for exclusive breastfeeding for at least six months completed the list of child-specific variable included.

Household covariates: First, household socioeconomic status is included in the model. Socioeconomic status is presented as composite wealth index that combines agricultural assets, housing quality and energy, water and sanitation and household durable asset endowments. Indices were developed in two stages using PCA (Filmer and Pritchett, 2001; Vyas and Kumaranayake, 2006). It is generally understood that wealth indices provide a robust measurement of socioeconomic wellbeing, especially in the absence of good consumption, expenditure and income data (Filmer and Pritchett, 2001; Filmer and Scott, 2012). Age of the mother, parental education, are also included following on studies that have shown that parental education is an important determinant of child health (Kumar and Modi, 2008; Vollmer et al., 2016). Household controls further include household diet diversity score, food adequacy, and employment type of both parents, household size, access to information, under-5 children as a proportion of household size, a dummy for having at least one CBHI participating neighbour, waiting time at the health facilities, interface with a TBA, number of a groups a household belonged to and household religious affiliation.

Village covariates: Village variables included dummies for village having a school, a health centre, being a banana cultivating village or a pastoralist village were included. The number of burial groups in the village and the distance from the village to the hospital were also included.

3.3.2 Identification strategy: Two Stage Residual Inclusion estimator

A large body of literature attests to the fact that insurance increases health care utilisation, simply because, for poor households, it removes financial barriers to access. It is assumed that more utilisation of health services should, in principle, lead to improved health. But such a causal relationship is difficult to establish because of endogeneity between health insurance and the health outcomes of the insured people (Levy and Meltzer, 2004, 2008). It is therefore imperative that analysis of health insurance effect on health outcomes convincingly deals with endogeneity. The identification strategy, therefore, utilised an IV approach to overcome these endogeneity problems (Angrist et al., 1996; Angrist and Imbens, 1995). Instead of the conventional Two-Stage Least Squares (TSLS) IV approach, a Two-Stage Residual

[2] See Annex C for a detailed description of the multiple imputation procedure.

Inclusion (2SRI), which is more robust in addressing endogeneity in health economics studies (Cai et al., 2011; Terza, 2017b; Terza et al., 2008)) was employed.

The treatment variable measured two related parts; namely the treatment and the treatment intensity. To estimate the effect of this kind of treatment, an alternative estimation of the 2SRI which combines these two parts was applied following Terza (2017a). It is a common occurrence that when treatment is offered, treatment intensity varies across the treated (Angrist and Imbens, 1995) but also the proportion of non-compliers is large and non-ignorable (Mullahy, 1998). In a case like this, Mullahy (1998) proposed a two-part model where the probability of the treatment, $Pr(y\,0|x)$ is estimated first (through a probability model like a Probit), and that $E[ln(y)|y > 0, x]$ and is a linear function of x (e.g., $E[ln(y)|y > 0, x] = x\beta$) is estimated as the second part. This is the same framework as Hurdle or Two-Part Model (Mullahy, 1998).

These two steps produce both the probability of the treatment and the predicted treatment intensity. Residuals are then manually generated and included in the second stage outcome model, as in Terza (2017a). One other convenience of a 2SRI model is the ease with which the tests of endogeneity are done, by observing at the behaviour of the residuals (Gibson et al., 2010; Pizer, 2009; Staub, 2009). It is important to make sure that the first stage F-statistic for the joint significance of the instruments meets the threshold level of 10 (Staiger and Stock, 1997; Stock et al., 2002; Stock and Yogo, 2005). While the 2SRI and similar Control Function methods are routinely applied in health economics analysis, the two-part models are a recent accessory. In recent theoretical advances Terza (2017a) uses Mullahy's smoking and birthweight data, (Mullahy, 1997, 1998), to analyse the effect of maternal smoking on birthweight.

3.3.3 The empirical model specification

Just like the maternal smoking example in Mullahy (1997), a large part of our sample were not enrolled in insurance ($x = 0$) and in addition, those whose treatment was taken have varying treatment intensities such that $x|x > 1 = 1, 2....$ This, therefore, requires a two part-part instrumental variable Probit model (Mullahy, 1998). To model the Two Stage Residual Inclusion (2SRI) model, we the guidelines detailed in Terza (2017a). In the first part of the two-part first stage of the 2SRI, we estimated the probability of participating in CBHI (α_1) by regressing the instruments and other covariates using Probit model.

$$\mathrm{CBHI}_j = \beta_0 + \beta_1 Z_j + \beta_2 X_j + \epsilon \tag{3.1}$$

Where CBHI_j is the treatment dummy corresponding with 1 if household j participated in CBHI and 0 otherwise, Z_j is a vector of the instruments used, X_{ij} stands for a vector of a child, household and village covariates included in the model, and ϵ is the error term.

Using this model in this first step of the first stage, we predict and stored the results for the probability of being insured. Let us call this probability α_1. In the second part of the first stage, we fit a Generalised Linear Model (GLM) on the treated (insured) sub-sample whose dependent variable is treatment intensity measured by the number of years of continuous insurance. This GLM model is specified with a Gaussian distribution and the default link identity, specifications for continuous outcomes.

$$\text{CBHI Years}_\text{i} = \beta_0 + \beta_1 Z_i + \beta_2 X_{ij} + \epsilon \tag{3.2}$$

Similarly, in this equation, we include in all the instrumental variables and all other covariates included in the model. From this second step of the first stage, we predict and store the mean years of insurance. We call this α_2. We derive the residuals η_i as the differences between the observed insurance intensity and the product of predicted insurance status and predicted mean intensity.

$$\eta_i = \text{CBHIYears}_\text{i} - \alpha_1 * \alpha_2 \tag{3.3}$$

The second stage of the 2SRI model, we fit a Probit model of the outcome (stunting prevalence) on insurance intensity all other covariates and the residual inclusion estimator.

$$\text{Stunted}_{ij} = \beta_0 + \beta_1 \text{CBHIYears}_\text{i} + \beta_2 X_{ij} + \beta_3 \eta_i + \epsilon^{2SRI} \tag{3.4}$$

We then reported average partial effects of the probit model of outcome (margins) to show the effect of insurance on child stunting. In these models, we controlled for individual child-specific variables such as child age, sex, if they took a vitamin A supplement in the last months, immunisations taken and others. We also controlled for household-specific variables such as education of the parents, household durable assets, agricultural assets and use of protected water sources. We further included a perception index developed from a principle components analysis that takes a single principle component from several dimensions of perceptions concerning health insurance. We then included several village level controls. Because we generate the residuals from the two first step stages, bootstrapping is recommended to obtain the correct standard errors (Wooldridge, 2010). We bootstrap up to 1,000 replications for all the estimated models.

3.3.3.1 A review of the instruments used in health insurance studies

Normally, finding suitable instruments for health insurance research is a daunting task and many studies completely fail in this regard (Chankova et al., 2010; Rajkotia and Frick, 2012; Sepehri et al., 2011; Wehby, 2013). Moreover, even when instrumental methods have improved in rigour, instrument validation remains a contestable issue by economists (French and Popovici, 2011; Rashad and Kaestner, 2004). Nonetheless, due to the difficulties and limitations of randomisation and the rarity of natural occurrences to facilitate natural experiments (Barrett and Carter, 2010; Sanson-Fisher et al., 2007), the use of IVs in health services research has increased in prominence (Cawley, 2015). In health insurance studies, instruments that have been used include: (a) variations of employment status and or firm size (Bhattacharya et al., 2011; Deb et al., 2006; Koc, 2011; Rashad and Markowitz, 2007; Thornton and Rice, 2008; Wagstaff and Lindelow, 2008; Zheng and Zimmer, 2008); (b) variations on community or state level enrolment rates or phased rollouts (Binagwaho et al., 2012; Fink et al., 2013; Galarraga et al., 2010; Jung and Streeter, 2015; Sosa-Rubi et al., 2009; Strobl, 2016; Trujillo et al., 2005; Wirtz et al., 2012; Woldemichael et al., 2016); (c) probability of enrolling in insurance (Bhattacharya et al., 2011); and (d) differences in enrolment requirements across regions (Gajate-Garrido and Ahiadeke, 2015; Pan et al., 2016). Other instruments have included: randomized offer of enrolment (Raza et al., 2016); strict eligibility cut-offs used in combination with a regression discontinuity design (Palmer et al., 2015); and membership in microfinance or other social support organisations (Jowett et al., 2004; Woldemichael et al., 2016). While literature gives several prospective instruments, finding appropriate instruments is hinged on a clear understanding of the process behind the variable of interest (Angrist and Pischke, 2009, p. 88). Strong instruments in some studies might not be applicable in other studies mainly because of the contextualised processes behind each data generation process. One example is the distance to health facilities (with different variations)- which is a common and credible instrument in studies undertaken in developed countries with a wide network of health facilities in close geographical proximity, but which might not work in developing countries with health facilities insufficient and scattered.

3.3.3.2 Our instruments

In the usual framework of IVs, two basic conditions need to be fulfilled; (1) that the instruments have a strong predictive association with CBHI status and that (2) they do not have any significant association with the outcome - level of stunting, such that the only effect of the instruments on the outcome is through the CBHI status. Three instruments are adopted, namely: (1) village CBHI demand rate (2) size of a burial group a household belonged to and (3) leader and social influence experienced by a household on the decision to enrol in CBHI. Using three instruments improves model efficiency (Chao and Swanson, 2005; Hansen et al., 2008; Roodman, 2009). We expound on the logic of each of these instruments here below.

Village latent CBHI demand rate: a common IV in health economics studies is aggregated prevalence of a treatment (such as insurance) at community or sub-national level. French and Popovici (2011) reviewed several papers in health-related research which used instruments of this nature, and Wong et al. (2012) used census subdivision rate of vaccination as an instrument for receiving an influenza vaccine while Stukel et al. (2007) used regional catheterisation rates as an instrument for a patient's probability of receiving a cardiac catheterisation treatment. In health insurance literature, Jung and Streeter (2015) used the fraction of individuals enrolled in insurance at the community level as an instrument for enrolling in insurance in China. The logic in this type of instrument is that the probability of an individual receiving a treatment is correlated with the rate at which the treatment is available in the locality of the individual.

Because these types of instruments are more applicable to larger samples mainly using administrative data, the intuition in which ours is constructed is slightly different. All the non-CBHI households were asked that if they had one opportunity of joining a group they did not already belong to, which village group they would join. Villages had on average 5.3 other groups such as women's groups, youth groups or other village savings and lending association groups. Joining another burial group is very restrictive and happens only in very limited situations and only when the groups belong to the same kin association. For instance, one group could have grown out of the other and members have strong kin associations. Expressing a wish to join a burial group in CBHI showed a household's latent demand. Village latent CBHI demand rate was therefore constructed as the ratio of uninsured households who wish to join an insurance-registered group in each village.

$$\text{Village CBHI demand rate} = \frac{\text{Non CBHI households wishing to join a CBHI burial group}}{\text{Total non CBHI households}} \tag{3.5}$$

The latent demand rate ranged from 0 to 75 percent.

Size of the burial group: Membership in a burial group was one of the basic requirements of enrolling in CBHI but the size of the burial group in which a household belonged to also mattered. Earlier research in this area showed that over 96 percent of the households belonged to a burial group (Musau, 1999). In this sample, all the respondents belonged to a burial group. In societies with egalitarian and mutual assistance arrangements, group sizes matter (De Weerdt and Dercon, 2006; Dercon et al., 2006). One way in which group size is important is that larger groups reduce the possible egalitarian preferences possibly because of reduced cohesion between the group members and free riding (Stahl and Haruvy, 2006). However, there is another side to large groups. Another strand of literature suggests that the larger the group the higher the per capita utility from risk sharing (Genicot and Ray, 2003).[3]

There are a number of ways in which the group size is expected to influence enrolment decisions. To enrol in CBHI, a household had to be a member of a burial group but not all burial groups could participate. One of the conditions for a burial group to participate in CBHI was to have at least 20 households and if the group

[3]We are also aware of literature with a neutral take on the size of the group as regarding to group contributions, such as Fafchamps and La Ferrara (2012). However, one major distinction with Fafchamps and La Ferrara (2012) is the urban nature of his sample. Conventionally, urban residents often have multiple social safety nets and have better access to these safety nets such as financial services. Therefore group sizes might matter more for rural residents than it does for urban residents

size was less than 30, all households in the group had to enrol. Another condition was that for large groups, at least 60 percent of the households have to enrol and 60 percent had to be more than 30 households. In practice, the scheme would prefer relatively larger groups since there is more risk pooling and some level of controlling moral hazard.[4] Moreover, the costs of monitoring in larger groups might be lower because members monitor each other (Carpenter, 2007). However, it can also be assumed that smaller groups would be more likely to enrol in CBHI because the smaller numbers of households would be relatively easy for coordination and leadership as well as putting in place sanctions for divergence from the norms and expected behaviours.

Another possible influence of group size is that of benefits that accrue to large groups. Genicot and Ray (2003) suggested that the larger the group the higher the per capita utility from risk-sharing. Due to a larger social support risk-sharing network, members of larger groups may be less likely to join CBHI. As found in other countries such as Ethiopia and Tanzania, burial groups often carry out other roles such as village saving and lending (Dercon et al., 2006). Members, therefore, are more likely to have a larger pool of resources for reciprocal informal insurance hence reducing their probability of formalising insurance status by enrolling in CBHI. The requirement of 60 percent minimum for a large group might also present some enrolment bottlenecks. It is plausible that for instance, a group of 100 households would fail to participate in CBHI if at least 41 of the member households oppose the enrolment decision. To put it in another way, it is presumably harder to gain consensus on group level decisions when a group is large and the only way to maintain group cohesion is not to enrol. With this thinking, it is expected a group size would have a negative association with enrolment status. Indeed, this is the kind of association found.

Leader and social influence: The third instrument is influence from leaders and other social contacts that may be experienced by households in the decision to enrol in CBHI. Leader and social influence is measured as a composite indicator of how households perceive influence from local leaders, neighbours, extended family, friends and other members of groups in which they belong. Respondents were asked five statements with Likert Scale responses ranging from 1 to 5; where 1 corresponded with "do not agree" and 5 corresponded with "completely agree".[5] Using PCA, these responses were reduced to one composite indicator of leader and social influence. Chatterji (2006) also used a perception instrument to study the effect of illicit drug use during high school on educational attainment.

[4] The preference to larger size groups does not however deter smaller groups which meet the lower bound requirement from participating

[5] The statements are (1) I learn from our neighbours about the things I do such as which community groups to join, (2) Village opinion leaders influence me about the programmes / groups I enrol in, such as insurance, (3) my friends and other extended family members influence my decision to enrol in insurance, (4) Enrolling in insurance as an individual household would be better than the current condition to belong in a group (5) The experiences of other community members with insurance gives me an idea on whether I should join insurance or not.

The validity of these instruments is hinged on how they meet the relevance condition and the exclusion restriction. Table 12 below, show the first stage and reduced form associations of the IVs with CBHI status and stunting respectively. All the three instruments had a strong individual association with CBHI status and their combination shows that this strong association is maintained as indicated in Model 1 of Table 12.

Table 3.2: First stage and reduced form associations

	(1) CBHI Status		(2) Stunting	
	Coeff	SE	Coeff	SE
Village CBHI demand rate	0.801	(0.620)	0.628	(0.459)
Social Influence	0.159**	(0.068)	−0.009	(0.043)
Size of the burial group	−0.018***	(0.004)	0.001	(0.003)
Constant	−0.046	(1.319)	−0.575	(0.886)
All other covariates	YES		YES	
N	464		464	

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

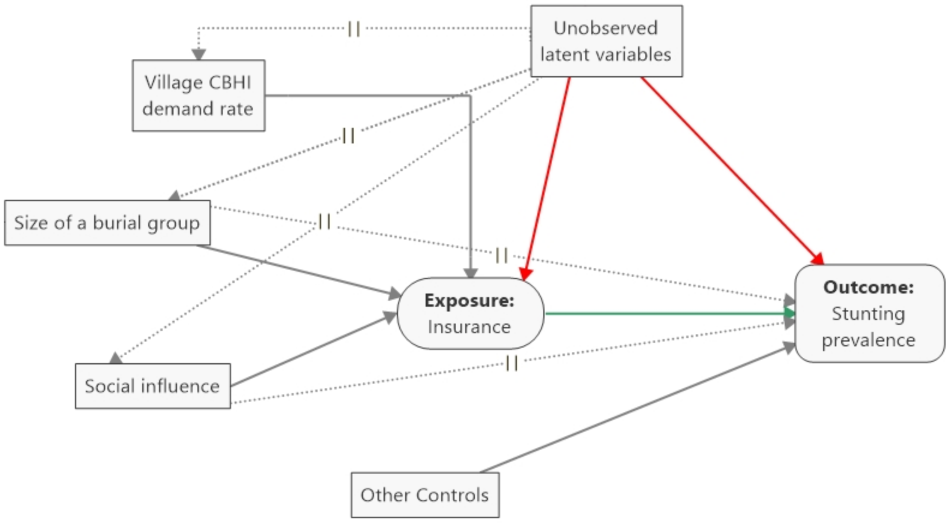
Given that we use more than one instrument, it is always advisable to check that none of the instrumental variables are correlated with the structural error term. Normally, the over-identification can be performed in a straight forward manner in other variations of the instrumental variable methods (estimating the Sagan or Hansen tests) but for our multi-step approach, we use a regression based approach that follows Wooldridge (2010, p 136-137). We estimate the equation:

$$\eta_i = \beta_1 Z_{ij} + \beta_2 X_{ij} + \epsilon \tag{3.6}$$

Where η_i are the first stage residuals, Z_{ij}'s and X_{ij}'s are the instruments and covariates respectively. From this equation we can obtain the over-identification test statistic which is N (our sample) times the R-squared, given as nR^2. OThe over-identification test statistic is 3.898 with an associated p-value of 1.000. The model, therefore, does not reject over-identification restrictions and any conventional levels

This causal relationship can be illustrated using Direct Acyclic Graphs (DAGs) (Stanghellini, 2004; Textor et al., 2017). The DAG below illustrates that the IVs are sufficient predictors of CBHI status, hence the causal link from the exposure to the outcome. It also depicts that there is no relationship between the IVs and stunting, also implying that the instruments influence the outcome only through the CBHI status.

Figure 3.1: DAG for causal association of CBHI membership and stunting



Source: Author's depiction

3.4 Results

3.4.1 Descriptive results

3.4.1.1 Health facilities' data

In order to precisely understand the differences between children in insured and non-insured households, the starting point is their birth conditions. For this purpose data of close to 3,600 children born between September 2010 and March 2015 in health facilities within our survey area was collected[6]. From this sample, 34.3 percent of the mothers were in insurance. There are significant differences in five of eight variables measured due to a household's / mother's CBHI status, as presented in Table 13. Mothers in insured households were older by 1 year and had about 0.5 more pregnancies than the uninsured. 44 percent of them were also assessed as better prepared for birth in that they arrived at the health facility at least one day before delivery. 73 percent of mothers with CBHI delivered normally while 78 percent of mothers with no insurance delivered normally. Caesarean section deliveries were the second common mode of delivery. This summary finding shows that insured mothers were more likely to deliver by caesarean section than uninsured mothers, a phenomenon that has been observed in other insurance programmes in developing countries such as China (Bogg et al., 2010; Long et al., 2012). There

[6]The smallest administrative area recorded in the birth registers is a parish, which comprises of several villages. However, we sampled villages for the household survey, implying that the sample for data collected from the hospital is much larger than the household survey sample

was no difference in the observed child's birthweight for mother with and without insurance.

Table 3.3: Differences between CBHI and non-CBHI mothers based on hospital data

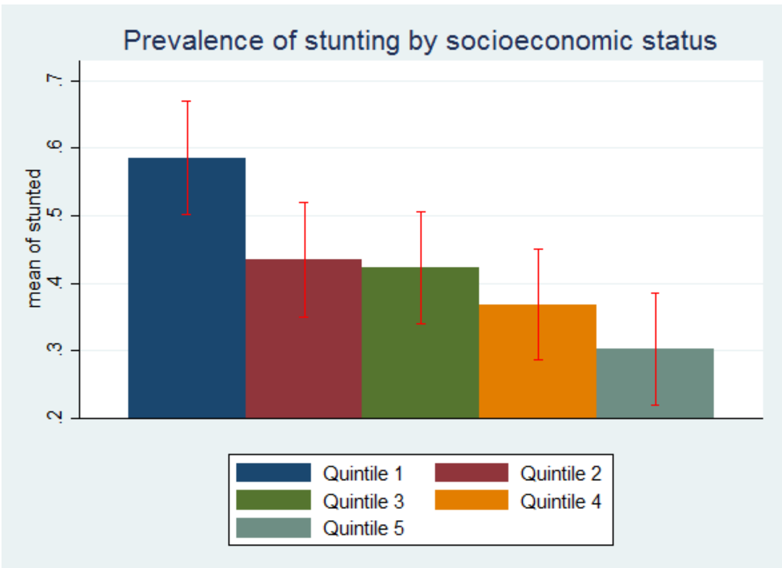
	Mean	Min	Max	SD	Mean insured	Mean uninsured	Mean difference	T-stat - istic
Insured	34.3	0	1	47				
Age of the mother	24.97	12	56	5.85	25.6	24.6	-0.951^{***}	(-4.64)
Birth weight	3.02	0.22	5.67	0.53	3.03	3.02	-0.0156	(-0.83)
No of pregnancies	2.84	1	12	1.99	3.2	2.7	-0.494^{***}	(-7.12)
Child is male	50.1	0	1	0.50	51.7	49.3	-0.0241	(-1.37)
Normal delivery	76.2	0	1	0.43	73.3	77.9	0.0491^{***}	(3.28)
Birth preparedness	41.9	0	1	0.49	43.9	40.8	-0.0311^{*}	(-1.79)
N	3595							

t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1,

3.4.1.2 Household survey data

Overall, 42.2 percent of the children in the sample were stunted. Stunting prevalence was similar to the average in south-western Uganda, 41.7 percent but higher than the national average of 33.1 percent, as in the 2011 DHS (UBOS and ICF International, 2012). In terms of the distribution of stunting, children in the lowest wealth quintile had a higher prevalence of stunting, of 58.5 percent while only 30.2 percent of children in the highest wealth quintile were stunted.

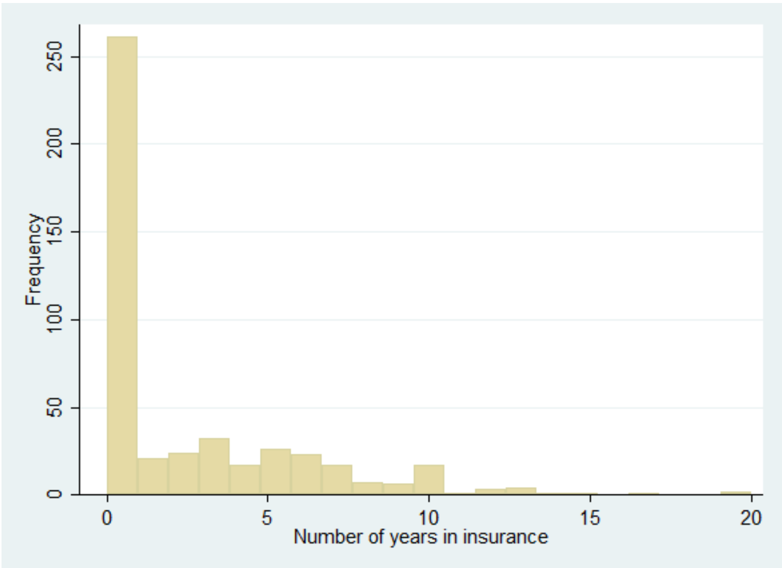
Figure 3.2: Prevalence of stunting by wealth quintile



43.8 percent of the households surveyed were enrolled in CBHI at the time of the survey. For CBHI participating households, the average length of continuous participation was 5.2 years. The distribution of years in CBHI was right-side calibrates to a maximum of 11 years because of a sparse distribution after 10 years. In 30.4 percent of the households, at least one of the parents had some secondary level education. The average age of mothers interviewed was 30.2 years while the average age of the children whose data was recorded was 30.2 months

Some 63.4 percent of the mothers had exclusively breastfed their youngest child for 6 months. Households had on average 0.4 LLINs per household member and only 55.4 percent of the births took place in health facilities. Though this was higher than the south-western average of 40.3 percent in 2011 (UBOS and ICF International, 2012), it was lower than the 2016 south-western average of 70.3 percent (UBOS and ICF, 2018).

Figure 3.3: Insurance Status



In terms of distribution of respondents by village economies, some 18.1 percent of the households were located in forestry villages while 26.1 percent were in banana cultivation villages. More descriptive statistics are presented in Table 14 below.

3.4.2 Empirical results

3.4.2.1 Main model results

The main empirical results are presented in Table 15 below. In order to make the appropriate comparisons, results for ordinary probit regressions. Models 1 and 2 show the average partial effects of the association of CBHI participation and intensity of CBHI as measured by the number of years in CBHI respectively, with

Table 3.4: Descriptive results

VARIABLES	Man	Min	Max	S
CBHI status	0.438	0	1	0.497
Years in CBHI	5.138	1	11	3.015
Child's age (months)	30.202	5.550	60.580	15.152
Mother's age (years)	30.204	14.010	56.540	7.164
Child is male	0.481	0	1	0.500
Birthweight	3.186	2.0	5.6	0.529
LLIN per capita	0.436	0	3	0.281
Exclusive breastfeeding	0.634	0	1	0.482
Health facility delivery	0.554	0	1	0.498
Catholic	0.504	0	1	0.501
Parental (some) secondary education	0.304	0	1	0.460
Wealth index				
Quintile 1	-1.280	-1.754	-0.999	0.193
Quintile 2	-0.784	-0.997	-0.565	0.123
Quintile 3	-0.286	-0.564	-0.052	0.153
Quintile 4	0.315	-0.051	0.766	0.254
Quintile 5	2.212	0.767	8.365	1.435
Food adequacy	0.534	0	1	0.499
Household diet diversity score	4.080	0	8	1.280
Husband's employment - casual labour	0.356	0	1	0.479
Mother's employment -casual labour	0.101	0	1	0.302
Household size < 4	0.401	0	1	0.491
Proportion of under five	0.265	0.077	0.667	0.129
Access to information	-0.000	-2.631	4.472	1.289
Neighbour in CBHI	0.692	0	1	0.462
Waiting time	88.621	5	540	108.851
No of groups' membership	1.829	0	5	1.003
Groups membership squared	4.351	0	25	4.198
Interface with TBA	0.528	0	1	0.500
No of burial groups in the village	5.601	1	10	3.349
Distance to hospital	11.239	5.45	17.40	3.349
No of household in the village	120.412	25	250	57.692
Village has a health centre	0.401	0	1	0.491
Village has a school	0.634	0	1	0.482
Village economy-pastoralism	0.192	0	1	0.394
Village economy-banana cultivation	0.261	0	1	0.440
Village CBHI demand rate	0.482	0	0.75	0.183
Social influence	-6.79×10^{-09}	-5.006	2.013	1.506
Size of burial group	71.366	18	200	26.054
Stunting	0.425	0	1	0.495
N		464		

Mean for years in CBHI corresponds to only the CBHI participating households (n=203). 44% of the variable birthweight (207 obs) are imputed, see imputation note the prevalence of stunting. After ascertaining that the models are well fit[7], results indicate that there was no statistically significant relationship between CBHI and stunting. The main focus is therefore drawn on the average partial effects of the 2SRI- IV results presented in Model 3. The average partial effects are in principle, the average treatment effects of a household participating in CBHI on stunting status of an under-five child. After implementing the second stage outcome probit regression of the probability of stunting, it is established that after controlling for all child-specific, household, and village level covariates, the probability of stunting reduces by 5.7 percentage points for each year a household is insured, significant at 1 percent.

Looking at other covariates that have a significant association with stunting, the socioeconomic welfare of a household assessed by the wealth quintiles, was also important in reducing child stunting. It was found that compared with the poorest quintile households, children in households within the second poorest quintile are able to reduce stunting by close to 19.4 percentage points, the third quintile by 14 percentage points and 19.1 percentage points for children within the fourth quintile households. While a statistically significant reduction in stunting for children in fifth quintile households was not observed, a large negative coefficient indicates that any move upwards in the welfare of the household was good for stunting reduction. In addition to household socioeconomic status, it was also observed that children in households of small sizes (of four members or less) were likely to reduce stunting by 11.9 by percentage points compared to children in relatively larger households.

Furthermore, it is found that the probability of child stunting increased by 3.2 percentage points as a child grew older. However, it increases in this probability started to reduce between 32 and 33 months. Two other main factors were noticed to increase the probability of stunting; exclusive breastfeeding and increase in the number of burial groups in a village. Stunting increased by 13.6 percentage points for children who had been exclusively breastfed for six months, a strange finding. An increase by 1 in the number of burial groups in the village was associated with increasing child stunting by 3 percentage points. The number of burial groups in a village might be taken to indicate the depth of traditional informal social support strategies which in turn limit households' formal insurance propensity.

A supplementary interest of this analysis was also to know how the probability of stunting changed for each additional year a household participated in CBHI. This gave a view of how the time aspect of CBHI intensity works. To know this, predictive margins by conditioning the regression to the categorical scale of CBHI participation are specified. The results, plotted in Figure 11 below indicate that the probability of stunting reduces consistently as households spend more years in CBHI. Specifically, it reduced from about 51.5 percent for children in households with zero years of CBHI participation to 37.6 percent in households with 5 years of consistent participation. The predicted probability was statistically significant

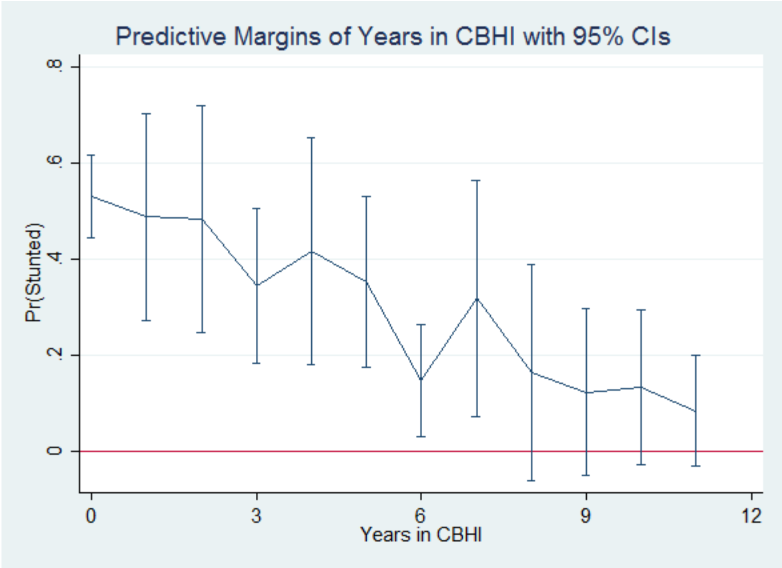
[7] Variance Information Factor (VIF) test for multicollinearity shows a mean VIF of 11.5 which is within the threshold of 30 (O'Brien, 2007; StataCorp, 2015) so we are confident that the models do not violate conventional multicollinearity standards. Both the linktest (Pregibon, 1980) and the goodness of fit (Hosmer et al., 2013) also show that the model is correctly specified.

Table 3.5: Impact of CBHI on stunting: Average Partial Effects

	(1)		(2)		(3)	
	Model 1: Probit		Model 2: Probit		Model 3: IV-2SRI	
	AP	SE	AP	SE	AP	SE
CBHI participation	0.038	(0.064)				
Years in CBHI			0.006	(0.009)	−0.057***	(0.022)
Child's age (months)	0.031***	(0.006)	0.031***	(0.006)	0.032***	(0.007)
Child's age square	−0.000***	(0.000)	−0.000***	(0.000)	−0.000***	(0.000)
Mother's age (Base: <24.9 years)						
25 - 34.9 years	−0.036	(0.056)	−0.042	(0.056)	0.027	(0.067)
35 - above	0.023	(0.073)	0.014	(0.073)	0.110	(0.086)
Child is male	0.022	(0.043)	0.023	(0.043)	0.028	(0.048)
Birthweight	−0.058	(0.042)	−0.060	(0.042)	−0.068	(0.046)
Health facility delivery	0.014	(0.048)	0.015	(0.048)	0.014	(0.053)
LLIN per capita	0.024	(0.082)	0.023	(0.082)	0.031	(0.100)
Exclusive breastfeeding	0.121***	(0.045)	0.121***	(0.044)	0.136***	(0.050)
Catholic	−0.062	(0.048)	−0.062	(0.048)	−0.054	(0.052)
Parental (some) secondary education	−0.071	(0.055)	−0.074	(0.054)	−0.077	(0.061)
Wealth index (Base: quintile 1)						
Quintile 2	−0.190***	(0.069)	−0.187***	(0.069)	−0.193**	(0.079)
Quintile 3	−0.177**	(0.070)	−0.177**	(0.070)	−0.140*	(0.081)
Quintile 4	−0.220***	(0.072)	−0.218***	(0.072)	−0.191**	(0.084)
Quintile 5	−0.204**	(0.084)	−0.201**	(0.084)	−0.152	(0.098)
Food adequacy	0.080*	(0.048)	0.080*	(0.048)	0.072	(0.056)
Household diet diversity score	−0.015	(0.019)	−0.014	(0.019)	−0.015	(0.022)
Husband employment - casual labour	0.013	(0.051)	0.014	(0.051)	0.019	(0.059)
Wife employment - casual labour	0.010	(0.073)	0.007	(0.072)	0.009	(0.084)
Household size <4	−0.135**	(0.055)	−0.137**	(0.055)	−0.119*	(0.062)
Proportion of under five	0.203	(0.218)	0.217	(0.219)	0.093	(0.250)
Access to information	−0.020	(0.021)	−0.021	(0.021)	−0.020	(0.024)
Neighbour in CBHI	0.009	(0.056)	0.009	(0.056)	0.036	(0.066)
Waiting time	−0.000	(0.000)	−0.000	(0.000)	−0.000	(0.000)
No of group memberships	0.000	(0.029)	0.002	(0.028)	0.050	(0.035)
Interface with TBA	−0.037	(0.050)	−0.039	(0.050)	−0.043	(0.057)
No of burial groups in village	0.010	(0.012)	0.010	(0.012)	0.029**	(0.014)
Distance to hospital	−0.014	(0.016)	−0.014	(0.016)	−0.031*	(0.018)
No of household in village	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)
Village has a health centre	−0.091	(0.096)	−0.089	(0.097)	−0.118	(0.110)
Village has a school	0.040	(0.075)	0.040	(0.075)	0.050	(0.087)
Village economy-pastoralism	−0.085	(0.102)	−0.085	(0.101)	0.010	(0.115)
Village economy-banana cultivation	0.006	(0.066)	0.008	(0.065)	0.038	(0.074)
Residuals					0.077***	(0.024)
Link test (hat squared)	−0.111	(0.185)	−0.120	(0.184)		
Mean VIF (uncentered)	11.55		11.51			
Goodness of fit chi square	0.1710		0.5278			
Pseudo R-squared	0.1226		0.1227		0.1407	
First stage Wald test					24.678	
N	464		464		464	

Robust standard errors in parenthesis for Models 1 & 2.
Standard errors for Model 3 in parentheses bootstrapped with 1000 replications.
Significance levels *** p<0.01, ** p<0.05, * p<0.1

Figure 3.4: Predictive margins of probability of stunting



until seven years in insurance. However, after the child's fifth birthday, stunting is no longer the appropriate measure of nutritional health but rather body mass index. In addition, it is also appreciated that other factors beyond the scope of this research and beyond the scope of household's individual efforts, also play a role in child welfare. Nonetheless, the reduction in stunting, causally associated with CBHI participation is very clear.

3.4.2.2 Some heterogeneous treatment effects

Boys and girls

The study was further interested in understanding the treatment outcomes between boys and girls by running separate models regressions. It is found that most of the stunting reduction was in boys. In particular, an extra year of participating in CBHI was associated with a 7.2 percentage point reduction in stunting among boys and only a 4.6 percentage point reduction among girls. Moreover, the coefficient of stunting reduction among girls was not statistically significant. Endogeneity was also controlled in the girls sub-sample. From summary results, it was found that stunting prevalence was 43.0 percent among males and 41.9 percent among females and the differences were not statistically significant. However, this indicated that boys were more likely to reduce stunting than girls. In addition, the effect of household socioeconomic status was strongest in the boys sub-sample only. Compared to boys in quintile 1, the probability of stunting for boys in quintiles 2, 3 and 4 was lower by 36, 28 and 36 percentage points respectively.

Local Average Treatment Effect

Imbens and Angrist (1994) suggested a precise measure of treatment effects, the lo-

Table 3.6: Effect of CBHI membership on stunting between boys and girls

	Model 1: Boys		Model 2: Girls	
	Coff	SE	Coff	SE
Years in CBHI	-0.0722^{*}	(0.0396)	-0.0462	(0.0417)
Child's age (months)	0.0280^{**}	(0.0129)	0.0376^{***}	(0.0119)
Child's age square	-0.0004^{**}	(0.0002)	-0.0006^{***}	(0.0002)
Exclusive breastfeeding	0.1589^{*}	(0.0916)	0.1388^{*}	(0.0794)
Catholic	-0.0698	(0.0962)	-0.0142	(0.0870)
Wealth index (quintile 1)				
Quintile 2	-0.3643^{**}	(0.1445)	0.0082	(0.1285)
Quintile 3	-0.2705^{**}	(0.1350)	-0.0061	(0.1392)
Quintile 4	-0.3601^{**}	(0.1504)	-0.0679	(0.1370)
Quintile 5	-0.2209	(0.1796)	-0.0844	(0.1556)
Food adequacy	0.1763^{*}	(0.0966)	-0.0149	(0.0914)
Household diet diversity score	-0.0655^{*}	(0.0391)	0.0130	(0.0372)
Household size <=4	0.0139	(0.1221)	-0.1861^{*}	(0.1004)
No of burial groups in village	0.0499^{*}	(0.0291)	0.0140	(0.0254)
Residuals	0.0831^{*}	(0.0431)	0.0721	(0.0460)
All other covariates	(YES)		(YES)	
N	(223)		(241)	

Standard errors bootstrapped with 1000 replications.
Significance levels *** p<0.01, ** p<0.05, * p<0.1

cal average treatment effect, which under mild assumptions, estimates the treatment effect on only the subjects who receive the treatment and not the whole population. To estimate this, the outcome regression similar to the one in the primary model was but undertaken but only on the subpopulation of the CBHI participant households. Results indicate that for the CBHI participating households, one extra year of CBHI participation was associated with reducing the probability of stunting by 14.8 percentage points, which was almost three times the effect in the whole population.

3.4.2.3 A comment on breastfeeding results

In these results, the finding regarding exclusive breastfeeding is intriguing. It indicates that the probability of stunting for children who had been exclusively breastfed was close to 14 percentage points higher. This is not the expected sign because exclusive breastfeeding is an integral component of child nutrition and anthropometric improvement (Kamudoni et al., 2007, 2015; Kuchenbecker et al., 2015). Moreover, exclusive breastfeeding in this study of 63.4 percent was not different from 63.2 percent reported in the 2011 DHS (UBOS and ICF International, 2012). It is therefore assumed that there was a possibility of a measurement error which can be explained in two ways. Measurement errors can be a result of a number of reasons

Table 3.7: Local average treatment effects

	Stunting prevalence	
	Coeff	SE
Years in CBHI	-0.1488^{**}	(0.0694)
Child's age (months)	0.0279^{*}	(0.0155)
Child's age square	-0.0005^{*}	(0.0002)
Mother's age (<24.9 years)		
25 - 34.9 years	0.3202^{***}	(0.1198)
35 - above	0.4490^{***}	(0.1585)
Birthweight	-0.1683^{*}	(0.0945)
Exclusive breastfeeding	0.2390^{**}	(0.1076)
Wealth index (Quintile 1)		
Quintile 2	-0.3432^{**}	(0.1741)
Quintile 3	-0.0857	(0.1919)
Quintile 4	-0.1519	(0.1845)
Quintile 5	-0.1024	(0.2332)
No of burial groups in village	0.0763^{**}	(0.0378)
Residuals	0.1520^{**}	(0.0688)
All other covariates	(YES)	
N	(203)	

Standard errors bootstrapped with 1000 replications.
Significance levels ***p<0.01, **p<0.05, *p<0.1

such as ambiguity of questions (Biemer, 2010) or social desirability bias in response (Grimm, 2010). For gender sensitive questions, the gender of the interviewer might also influence the response (Flores-Macias and Lawson, 2008). In some instances, respondents can also fail to recall the correct information if the events took place a considerable time before the survey (Kjellsson et al., 2014). For this survey, all the data collection assistants were well-trained females, fluent in the local language and supported by a trained nurse. The effect of gender in response bias, if any, might be ruled out.

Some public health and maternal health experts believe that data on exclusive breastfeeding is contentious and could sometimes be unreliable (Aarts et al., 2000; Cupul-Uicab et al., 2009; Gillespie et al., 2006; Greiner, 2014). Some suggest that the question 'exclusive breastfeeding at six months' should not be used at all due to the way in which it is framed (Debra, 2011) hence pointing to ambiguity related errors. A possible error might have been largely a recall error. After several years, mothers do not exactly remember for how long they breastfed their children and exclusive breastfeeding might be overstated (Aarts et al., 2000; Bland et al., 2003; Gillespie et al., 2006) and unreliable especially when a mother has had more children (Cupul-Uicab et al., 2009).

The other dimension of measurement error might be a social desirability bias (Grimm, 2010) that might be expressed in form of deception, under-reporting or over overestimating responses (Martinelli and Parker, 2009). This type of bias has been suspected in a malaria control study in Uganda which included a site close to where this very study was conducted. (Kamya et al., 2015) studied the parasitic prevalence and malaria incidence in households where children under 5 years had been given LLINs. An evaluation of malaria incidence found that at two study sites, reported LLIN usage rates were between 51 percent and 78.5 percent but episodes of malaria ranged from 182 to 1,546 over a 2 year period. Most intriguingly, the study site where the highest LLIN usage of 78.5 percent was reported, also had the highest episodes and the highest malaria incidence rates of 2.8 incidences per person per year. This was a paradox which (Meshnick, 2015) attributed to recall biases. Such social desirability might be at play with exclusive breastfeeding in this survey.

The worst-case scenario for these errors might be that the variable significantly drive the results. In view of this such a scenario, further analysis excluding the variable and compare the results. Results shown in Table 19 below indicate that once the variable exclusive breastfeeding is excluded from the model. The point estimates increase by 6.2 percent, from -0.057 to -0.060, a very marginal change.

Table 3.8: Results with and without exclusive breastfeeding

	(1) Incl. Breastfeeding		(2) Excl. breastfeeding	
Years in insurance	-0.0566^{***}	(0.0218)	-0.0601^{***}	(0.0222)
Exclusive breastfeeding	0.1355^{***}	(0.0498)		
Residuals	0.0769^{***}	(0.0240)	0.0817^{***}	(0.0243)
All other covariates	YES		YES	
N	464		464	

Standard errors bootstrapped with 1000 replications.
Significance levels ***p<0.01, **p<0.05, *p<0.1

It could be possible that with a sufficiently large sample, leaving out the variable exclusive breastfeeding would probably not have any credible change in the point estimates. However, in our relatively smaller sample leaving it out affects the results marginally. Moreover, early childhood nutrition including exclusive breastfeeding in the first six months is very important for child stunting so omitting it would cause even larger biases in the results. It is therefore recommended that future studies look into more precise ways of measuring exclusive breastfeeding to reduce possible measurement errors.

3.4.3 Robustness checks

Even when insurance uptake has increased over the years, only 43.8% of our sample were insured. The implication of this is that we have a large number of zeros in our data and hence there is over dispersion in our data. For robustness checks we therefore elicit to use alternative models which are consistent with count data with large number of zeros. Normally, count data is analysed with Poisson models, however due to substantial number of zeros in the data, zero inflated models such as Zero-inflated Poisson and Zero-inflated negative binomial models have been developed to deal with this kind of distribution, zero or non-zero and over dispersion of the count variables (Cameron and Trivedi, 2009, Chap 17). To compare with our main model, (which following Terza (2017a) also uses Generalised Linear Model (GLM) probit specifications) we estimate a zero-inflated Poisson and zero-inflated negative binomial model, which performs better with highly dispersed data (Hu et al., 2011). Comparing the results, we find that both alternative models produce similar results and account for endogeneity with similar level of efficiency. Our main coefficient is however 14 percent larger than the comparative models. Nonetheless, we are confident that even using different but suitable specifications, the similar results can be arrived at.

Table 3.9: Robustness checks with alternative specifications

	(1)		(2)		(2)	
	Main Model		First stage ZIP model		First stage ZIP model	
Years in CBHI	-0.057^{***}	(0.022)	-0.049^{**}	(0.021)	-0.049^{***}	(0.019)
Residuals	0.077^{***}	(0.024)	0.069^{***}	(0.023)	0.069^{***}	(0.020)
All other covariates	YES		YES		YES	
N	464		464		464	

Bootstrapped standard errors in parentheses.
Significance levels ***p<0.01, **p<0.05, *p<0.1

3.5 Discussion and conclusion

It is of interest to explore the mechanism through which these effects on stunting suffice. A couple are explained. The first one is the social network and social learning platform that burial groups provide hence facilitating the adoption of health interventions and behaviours for improving health such as health insurance. For instance, it is found that households that had more social networks were more likely to improve sanitation and hygiene in India (Shakya et al., 2014, 2015). Such social networking is important in changing health behaviours through receiving health information, adoption of preventive health information and ultimately leading to improved health. A series of papers on a long-term river blindness intervention in the same region as one in which this study takes place underline the usefulness of burial groups in reducing river blindness through acting as points of learning and information diffusion (Katabarwa et al., 2010a,b, 2000b).

There are a couple of ways in which social learning might be facilitated. The first one is in the length of participation in CBHI in that the longer a household stayed in CBHI, the more learning and behaviour change. This is captured by the chosen estimation strategy that not only considers the current insurance status of the household but also the length of insurance. The other mechanism through which social learning might happen is through the intensity of group activities, especially group meetings. The intensity of groups meetings provides an opportunity for more learning and information diffusion. In this study, it was found that burial groups participating in CBHI met on average 14 percent per month more (2.36 times versus 2.07 times). It is therefore posited that more exposure to group activities would be associated with more learning. Studies in Zambia (MacIntyre et al., 2012) and Nigeria (Kilian et al., 2016) have posited that intensive exposure of households to information regarding uptake of mosquito nets highly influences their probability of uptake. Insurance experience in this case study somehow mirrors these two dimensions of social learning impact pathway.

Savings, consumption and investment are other channels through which such effects might happen. Studies from other developing countries have found that health insurance was associated with increases in both food and non-food household consumption (Bai and Wu, 2014; Wagstaff and Pradhan, 2005). These studies build on the large body of literature on the effect of insurance on financial protection. The framework is that households who are insured are financially protected from catastrophic health expenditures and therefore able to re-channel savings into food and non-food consumption. Unfortunately, the data collected in this study did not have a detailed consumption and expenditure module so what is available can only be used speculatively. All the households were asked about their income in the last 30 days and the amount of money they paid at a health facility for the most recent visit. OLS regressions of the association between CBHI participation and household income and between CBHI participation and reported health expenditure, show, as would be expected, significant negative associations between CBHI participation and health expenditure while there was no significant association between CBHI and household income. This indicates that households in CBHI were more likely to incur lower health expenditures and hence save more.

Whilst this pathway is less than conclusive because of the limited reliability of stated income data, it is a close indication that there might be some saving and financial protection going on as a result of enrolling in CBHI. Households can, therefore, spend on other food and non-food items (Bai and Wu, 2014; Wagstaff and Pradhan, 2005) which can improve the health of children and other household members.

The final channel that is postulated is through health service utilisation. Many studies have found that health insurance coverage greatly facilitates utilisation of health services for mothers (Wang et al., 2016) and for children (Gajate-Garrido and Ahiadeke, 2015; Singh et al., 2015).[8] Findings from this study are in line with this literature. For instance, CBHI participating mothers were more likely to have four or more antenatal care (ANC) visits, receive the essential ANC services and have a postnatal care visit compared to non-participating mothers. Moreover, when asked if a child had experienced sickness conditions manifesting in a cough, or fever or diarrhoea in fourteen days prior to the survey, only 3.5 percent of children in insured households reported the affirmative compared to 6.1 percent of the children

[8] The next chapter also looks into the utilisation question, focusing on preventive health services.

Table 3.10: Association of CBHI participation with household income and health expenditure

	(1) LogIncom	(2) LogIncom	(3) LogCar	(4) LogCar
CBHI participation	-0.0320		-1.1648^{***}	
	(0.1243)		(0.1790)	
Years in CBHI		0.0104		-0.1267^{***}
		(0.0163)		(0.0323)
Constant	10.6622^{***}	10.6239^{***}	9.9964^{***}	9.7315^{***}
	(0.0858)	(0.0753)	(0.1136)	(0.1108)
R Squared	0.0001	0.0008	0.1214	0.0740
N	464	464	304	304

Robust standard errors in parentheses.
Significance levels ***p<0.01, **p<0.05, *p<0.1

in uninsured households. These differences give a compelling correlation through which health services utilisation can translate into health improvements.

Table 3.11: Differences in services utilisation as pathways of impact

	(1) Overall mean	(2) Mean CBHI	(3) Mean Non CBHI	(4) Mean difference	(5) t-statistic
Attended at least 4 ANC visits	71.55	89.16	57.85	-0.313^{***}	(-7.88)
Attended at least 1 postnatal visit	82.76	84.73	81.24	-0.0350	(-0.99)
Received essential ANC services	40.73	50.25	33.33	-0.169^{***}	(-3.73)
Reported the 3 child illnesses	4.96	3.45	6.13	0.0268	(1.32)
N	464	203	261	464	

Significance of the mean difference reported for ***p<0.01, **p<0.05, *p<0.1

In conclusion, this chapter utilises a novel IV approach following Terza et al. (2008); Terza (2017a) to study the effect of CBHI on child stunting. This IV approach is not only suitable for health economics analysis of non-linear outcome nature but it also facilitates the combination of the treatment (CBHI participation) and treatment intensity (length of participation measured in years) to estimate the effect. The results reveal that on average, CBHI reduces the probability of stunting by up to 5.7 percentage points for each year a household participated in CBHI. This implies that children who are born in households participating in CBHI and remain so until the children are five have the probability of stunting reduced by over 28 percentage points. In a country where about one-third of all under-five children were stunted, such reductions were profound. Current and future policy discussions should consider promoting this kind of insurance in rural areas not only to mobilise more resources for health systems but also for its contributions to improving child health. However, it was found that a large part of this effect was dominated by boys over girls as boys reduce stunting in larger and statistically significant margins than girls. This raises the concern and the need to focus more on girls and women who do not often have equitable access to health services. It will be important to gather more evidence on the health outcome impacts of health insurance so that these can be put into consideration when CBHI and other kinds of health insurance are promoted to target populations.

CHAPTER

FOUR

EFFECT OF COMMUNITY-BASED HEALTH INSURANCE ON PREVENTIVE HEALTH: AN ANALYSIS OF SELF-REPORTED USE OF PREVENTIVE HEALTH INTERVENTIONS.

4.1 Introduction: Community-based health insurance and preventive health

Community-based health insurance (CBHI) schemes are a kind of health insurance arrangements emanating from existing social support systems, often working in the informal sector and rural areas in developing countries (Bennett et al., 1998; Criel et al., 2004) In many instances, membership in these schemes is voluntary and often depends on existing or previous social support systems such as burial groups, mainly operating on mutual support and non-profit platforms (Dercon et al., 2004, 2006; Katabarwa et al., 1999). Over the last few decades, CBHI schemes have become integral in health systems landscapes of developing countries, with support from the WHO and national governments. The WHO World Health Report 2010 identifies CBHI as an important health financing mechanism (WHO, 2010) and scholars suggest that they can become essential building blocks for improving health delivery in developing countries (Bennett et al., 2010; Wang and Pielemeier, 2012). Several developing countries have therefore embraced CBHI and in some like Rwanda, almost reaching universal coverage (Fenny et al., 2018).

From a research perspective, the impact of CBHI (and broader health insurance) has been explored in several dimensions (such as effects on financial protection, utilisation of health services and quality of health services), however, there remains a dearth of evidence on how it affects utilisation of preventive health services and strategies. A number of studies, mainly from Latin America (Bitrán et al., 2010; Cercone et al., 2010; Giedion et al., 2010; Miller et al., 2013b; Pagan et al., 2007) have analysed the effect of health insurance on a range of preventive health outcomes, but while the evidence is still limited, it is also mixed. Moreover, in sub-Saharan Africa, the evidence is almost non-existent, bar Yilma et al. (2012) in Ghana. In view of this limited exposition on the possible effects on preventive health, a couple of questions remain unanswered. For instance, are certain preventive health behaviours nudged due to insurance membership? Does diffusion of preventive health knowledge and practices happen and saturate to cause behaviour change in households in insurance? Can the capacity of CBHI groups be leveraged to advance preventive health and reduce disease prevalence in the target population?" This chapter seeks to narrow this gap with a focus on CBHI in south-western Uganda.

Using cross-sectional data on a relatively large CBHI scheme from rural south-western Uganda, Inverse Probability Weighting (IPW) on the propensity score was applied to study the effect of membership on a range of preventive health treatments and home-based strategies. Results strongly indicate that CBHI has substantial positive impacts on preventive health treatments and practices. In particular, the study found that enrolment in insurance was causally associated with increasing the probability of using an LLIN net by 28.5 percentage points, household water treatment by 20 percentage points, iron supplementation by 13.1 percentage points and deworming by 23.4 percentage points. Significant average treatment effects on the treated (ATET) were also found regarding LLIN, handwashing, iron supplementation, deworming and PCV vaccination to prevent childhood pneumonia. It is taken that most of the effect was through social network effects related to learning and information diffusion. It is further posited that the length of time of CBHI participation was essential for learning and behaviour change. There were also other supplementary services, such as community health promotion, which though not related to insurance provision, are provided through the same channels as insurance and therefore give insured households an edge.

The rest of this introductory section gives a brief overview of preventive health in Uganda. Further on, Section 4.2 provides a contextual understanding and the importance of preventive health in developing countries. In this section, the literature on other interventions to nudge take-up of preventive interventions is reviewed. Section 4.3 focuses on the theoretical framework using Dupas (2011b) model of investments in preventive health and an exposition of the IPW framework. Section 4.4 presents the results of average treatment effects (ATE) and ATET, and these results are discussed concurrently. The concluding Section 4.5 summarises the chapter and makes some policy-relevant comments.

4.1.1 Preventive health in Uganda

The provision of preventive health services in Uganda is synchronised with the existing policy of financing health services that stipulates free access to health services (Nabyonga Orem et al., 2005, 2011). The government health financing policy is however implemented in public (government owned) facilities whereas private facilities are allowed to charge user fees.[1] Private-not-for-profit (PNFP) health facilities receive government grants to provide primary health care services, including essential maternal and child health services, at subsidised costs (Amone et al., 2005; Okwero et al., 2010). Budget documents reviewed reveal that about 40 percent of primary health care budgets are allocated to PNFP facilities in grants for these services. It is estimated that these grants account for about 22 percent of the overall financing for PNFP facilities (MOH et al., 2012). Regarding availability, a recent report on service availability indicated 93 percent offered preventive services for under-five children, including vitamin A supplementation (88 percent), iron supplementation (82 percent) and deworming (93 percent) (MOH, 2013). A number of other services such as LLINs are also provided by the government and donors, at zero direct cost to the households. For instance, between 2013 and 2014, 22 million LLINs were distributed across the country (USAID, 2015).

This background helps to postulate the kind of effects expected, given that there is no or limited direct cost to access preventive health services and that the costs do not necessarily arise from the point (public or PNFP) of care. Two kinds of effects are, therefore, expected; (a) home-based behaviour change effects for the utilisation of home-based preventive strategies such as water treatment, handwashing and using of long-lasting insecticide nets (LLINs), and (b) utilisation of clinically provided preventive services such as deworming or PCV vaccine. These require households

[1] Private health facilities, especially non-profit facilities, make a substantial proportion of health infrastructure. For instance, of the 152 hospitals in Uganda in 2012, 42.7 percent were private not for profit hospitals while 42.1 percent were public (government)(MOH, 2012).

to make an effort to access the health facility or health outreach post in order utilise these services.

Since preventive services are available and subsidised, it would be assumed that their utilisation is high. In fact, it is the opposite. Uganda, like many developing countries, has a big burden of preventable illnesses. For instance, malaria infection rates are estimated between 3.6 million (WHO, 2017a) to 13 million per year (WHO, 2016). A recent report shows that malaria remains the leading cause of death among under-fives, accounting for 43 percent of all under-five deaths (MOH, 2016a). However, while ownership of LLINs has increased to 78 percent (UBOS and ICF, 2018) prior evidence suggested that less than half of the households who owned an LLIN actually slept under them (Ahmed and Zerihun, 2010). Moreover, the direct cost to households of accessing LLINs is very low. In 2014, 22.3 million LLINs were freely distributed across the country (USAID, 2015) and 24 million more were distributed in 2016 and 2017 (MOH, 2016b). Diarrhoea and pneumonia (and other acute respiratory infections) also account for 23 percent of under-five deaths in Uganda (WHO, 2015). Only 39 percent of the population has access to an improved sanitation facility[2] and only 59 percent have hand washing facilities (UBOS and ICF, 2018). Over 90 percent of the population is constantly exposed to biomass pollution leading to a prevalence in chronic obstructive pulmonary disease of over 16 percent (Van Gemert et al., 2015), which can be reduced significantly by adopting energy saving stoves.

4.2 Preventive health and strategies for uptake in developing countries

4.2.1 What is preventive health and why is it important?

Kenkel (2000) defines the general scope of preventive health as a range of services classified into three main categories, namely; primary prevention, secondary prevention, and tertiary prevention. Primary prevention refers to actions that reduce the occurrence or incidence of disease that include but are not limited to vaccinations, clinical care, and advice (such as antenatal and postnatal services), nutrition and sanitation. Secondary prevention refers to actions to limit the health consequences of a disease such as screening for chronic illnesses which allow for early detection and management. Tertiary prevention refers to actions to reduce disability associated with chronic illnesses. For the purpose of this study, preventive health is narrowed to ex-ante services before the onset of detrimental health conditions (Kremer and Snyder, 2015) and hence limited to only primary prevention in Kenkel (2000)'s scope of services. Such services include, for instance, sleeping under LLINs which prevent malaria, treatment of water for household use which prevents waterborne diseases, taking deworming tablets which prevents intestinal worms and immunisation which prevents diseases such as polio, measles, and tuberculosis.

[2]including improved but shared toilet facility

Clean water and improved sanitation (Plotkin and Plotkin, 2013), as well as immunisation, are essential for preventing a range of common illnesses in developing countries (Andre et al., 2008; Bloom et al., 2005). The commonly used routine childhood vaccines; such as Bacillus Calmette- Guérin (BCG), diphtheria-tetanus-pertussis (DTP), and measles vaccines, are important in enhancing child immunity and reducing all-cause child mortality (Higgins et al., 2016). Rotavirus vaccine, a preventive vaccine for diarrhoea can eradicate up to 28 percent of severe diarrhoea (Fischer Walker et al., 2013) while pneumonia vaccinations can avert more than one million pneumonia-related deaths in developing countries (Madhi et al., 2008). Randomised controlled trials have also found that vaccines have further non-specific positive effects on child health that are not directly attributable to specific diseases targeted (Aaby et al., 2010; Benn et al., 2013; Rasmussen et al., 2016), including improvements in anthropometric indicators (Aaby et al., 2012; Anekwe and Kumar, 2012).

Childhood and adult morbidity can be further reduced by simple behavioural actions such as handwashing after using toilets and before and after eating. For instance, studies in Pakistan found that handwashing reduced the incidence of pneumonia by 50 percent and diarrhoea by 53 percent (Luby et al., 2004, 2005). Hookworms and other helminth infections can be eradicated by periodic preventive deworming chemotherapy (Addiss, 2015; Albonico et al., 2008; WHO, 2006), and health education and improved sanitation can reduce contamination and spread of disease-causing pathogens (WHO, 2017b).

4.2.2 Disease burden from preventable illnesses in developing countries

It is important to focus on preventive health because a large proportion of developing countriesŠ disease burden is composed of such easily preventable illnesses. Statistics on the disease burden of preventable illnesses are astounding. For instance, while all the other regions have advanced in providing safe drinking water, 663 million people in Sub-Saharan Africa still lack access to safe drinking water (WHO, 2015). An estimated 1 billion people around the world, more than 60 percent of them in India, defecate openly (Burki, 2015). Lack of access to safe water and sanitation facilities is one of the major causes of preventable illnesses such as diarrhoea and pneumonia (Pruss-Ustun and Corvalan, 2006). It is estimated that in 2011, over 36 million episodes of diarrhoea accounting for 700,000 childhood deaths happened globally, with nearly 75 percent of diarrhoea mortality happening in only 15 low-income countries in sub-Saharan Africa and south-east Asia (Das et al., 2014; Fischer Walker et al., 2013). Similarly, over 14 million episodes of sanitation-related pneumonia resulted in 1.3 million mortalities in 2011 (Fischer Walker et al., 2013).

Malaria retains a considerably large disease burden in the developing world. A recent global Malaria Status Report (WHO, 2016) indicated that in 2015 212 million morbidity cases and up to 639,000 mortality cases were registered worldwide and 90 percent of morbidity and 92 percent of mortality were in sub-Saharan Africa alone. Another issue that probably does not receive much focus and attention in preventive health services is the effect of indoor pollution from biofuels. This is associated with respiratory illnesses such as tuberculosis and asthma, which have a disproportionate effect on women and children (Franklin, 2007; Zar and Ferkol, 2014). It is estimated by the WHO that about 1.6 million deaths, accounting for about 38.5 million disability-adjusted life years, are attributed to indoor smoke caused by the use of solid fuels (Torres-Duque et al., 2008). Last but not least, soil-transmitted helminthiasis and other worms also present a public health crisis with an estimated infestation in about 24 percent of the worldŠs population or about 1.5 billion people (WHO, 2017b). These are just some of the many examples of illnesses that are easily preventable and yet affecting a significant population in developing countries.

4.2.3 Low uptake of preventive health strategies

Despite the benefits of interventions such as immunisation, and the high disease burden of preventable illnesses, uptake of interventions that prevent and reduced illness is often low. Rainey et al. (2011) estimated that over 1.4 million child death in 2006 occurred from vaccine-preventable illnesses. This was attributed the significant proportion of unvaccinated or under-vaccinated children, mainly in developing countries. Moreover, even among the children who are vaccinated, a substantial portion do not receive vaccinations on time, yet timely vaccination is important for attaining maximum protection. In The Gambia, for instance, a 2011 study found that 63 percent of children did not receive their vaccinations at the right age (Odutola et al., 2015). Another study conducted in Eastern Uganda between 2006 and 2008 found that only 18 percent of children received the required vaccinations within the recommended age (Fadnes et al., 2011). This situation is closely similar across many developing countries (Clark and Sanderson, 2009).

Apart from vaccinations, uptake of other preventive health strategies is also un impressive. In 2015, only 31 percent of eligible pregnant mothers received three or more doses of intermittent preventive treatment of malaria during their pregnancies (WHO, 2016). An inability to receive preventive treatment during pregnancy might be a supply-side challenge (Rassi et al., 2016), but demand-side bottlenecks also remain prominent. Reports of misuse of LLIN for instance for fishing (McLean et al., 2014; Minakawa et al., 2008) are not just trivial but reveal a wider disregard of preventive health interventions. Over one billion people in developing countries, a trend that has shown minimal improvement in the most endemic countries still practice open defecation (WHO, 2015). Due to low take-up of such preventive strategies, a number of strategies and interventions have been designed and implemented to facilitate improvements. These strategies and interventions are examined the following section

4.2.4 Improving uptake of preventive health interventions

In a detailed review of literature about investments in preventive health, with a focus on developing counties, Dupas (2011b) classifies interventions to nudge take-up of preventive treatments in two categories, namely; (1) interventions using education, information and social learning and, (2) those targeting behaviour change through demand and supply, including mechanisms for financing both demand and supply. First, interventions using education, information and social learning are examined.

Households may not demand and use preventive interventions because they do not have appropriate and adequate information. The information question has been studied widely in various interventions such as household water and sanitation in South Asia(Jalan and Somanathan, 2008; Madajewicz et al., 2007; Luby et al., 2004, 2005), HIV infections among teenagers (Dupas, 2011a). The main finding in these studies is adequate and appropriate information facilitates behaviour change to adopt preventive interventions. But in some instances, even with information access, deeper perception changes are required for a targeted population to change behaviour, a point that Mobarak et al. (2012) underline regarding households' low uptake of improved cookstoves in rural Bangladesh.

Education and information can circulate through social learning in networks. A body of research is emerging on social learning and adoption of preventive treatments in developing countries. (Shakya et al., 2014, 2015) have studied the social network effect in the decision to own latrines in Indian households and another experiment is currently underway in Honduras on improving maternal and child health treatment seeking behaviour through social network axioms (Shakya et al., 2017). Onnela et al. (2016) found that decisions to take polio vaccine in the Malegaon region of India were significantly influenced by the social ties a household was associated with while Apouey and Picone (2014) found social interactions important in malaria prevention in 29 sub-Saharan countries.

However, even in the presence of education and social learning instruments, uptake might remain low due to affordability reasons. In many situations, populations targeted for these interventions are also poor with significant liquidity constraints and low demand capacity. Studies have shown that initial costs of acquisition of some health technologies can be prohibitive in the decision to adopt appropriate technologies. This is the main reason found by Bensch et al. (2015) and Cundale et al. (2017) regarding adoption of improved cooking stoves in Burkina Faso and Malawi respectively. In order to raise the capacity to demand in such populations, several instruments have been suggested. These include and might not be limited to, cash transfers, vouchers and price subsidies for particular treatments and health products. Kremer and Miguel (2007) and Cohen and Dupas (2010) studied the effect of price subsidies for deworming and LLIN use respectively in Kenya. Both findings indicate that preventive health products were price elastic, even when the prices were significantly lower than the market prices. Given that these products have at least cost recovery targets, the extent to which subsidies can be introduced at a level that achieves some cost recovery while not economically prohibitive to target populations is critical (Ahuja et al., 2015; Dupas, 2014).

Liquidity constraints can also be eased through providing households with additional income through cash transfers or vouchers. Voucher interventions have been implemented in many countries for different purposes (for instance Dupas (2009) regarding LLIN adoption in Kenya, Kanya et al. (2014), Jehan et al. (2012) and Van de Poel et al. (2014) on maternal health services among others) and evaluations largely conclude that vouchers increased uptake of preventive strategies like antenatal care visits and delivering in health facilities. Studies evaluating the use of cash transfers also find that households who received a cash transfer were more likely to utilise preventive health services and treatments more than those who did not[3]. However, cash transfers, vouchers and subsidies have significant implementation bottlenecks regarding exclusion and inclusion (Kidd, 2017; Mishra and Kar, 2017). Dupas et al. (2016) suggest that an optimum mix of free products and prices can achieve coverage and adoption with limited exclusion and inclusion errors. In practice, however, multiple instruments used in one population is complicated for broad implementation. The success of these demand inducing instruments, therefore, depends by and large on how good targeting is done (Devereux et al., 2017; Sabates-Wheeler et al., 2015) with caution and not to destabilise community harmony (Ellis, 2012)[4]. In the case of subsidies, while higher subsidies would be preferred, evidence suggests that there would be significant wastage as most of the subsidies are taken by people who do not essentially need them (Cohen et al., 2015).

These challenges in implementation, both for demand inducing and information instruments, notwithstanding, interventions to improve uptake of preventive treatments do not achieve expected and long-lasting impacts and raise sustainability questions. For instance, in communities with endemic open defecation, sanitation interventions achieve only marginal results and disease burden hardly changes, as Patil et al. (2015) found in a randomised study in India. In a systematic review including 64 studies, Garn et al. (2017) found that improvements in latrine ownership and use were only modest after sanitation interventions. In some areas in Ethiopia, one year after implementation of a community participatory sanitation intervention, open defecation increased by 8 percent (Crocker et al., 2017). Crocker et al. (2017) called for sustained training of extension workers and local actors, and the combination of sanitation with other interventions, if the gains were to be sustained.

Even in cases where progress is registered, recent evidence suggests that researcher should worry about response biases in evaluation surveys (Meshnick, 2015). For instance, Luoto et al. (2014) found that whereas 70 percent of the households in Kenya self-report the use of chlorine for water treatments, only half of these had a

[3]These include but are not limited to Cecchini and Soares (2015) in several Latin American countries, Thornton and Rice (2008) in Malawi, Morris et al. (2004) in Honduras, Barham et al. (2007) in Mexico and Nicaragua, Amarante et al. (2016) in Uruguay, Robertson et al. (2013) in Zimbabwe among others

[4]Another way of easing liquidity constraints is through providing loans to target populations. Fink and Masiye (2015) look at adoption of LLIN through agricultural loans to farmers in Zambia and Tarozzi et al. (2014) evaluate LLIN uptake through micro-loans in India

positive test when the tests were conducted. This essentially leads to wastage as Cohen et al. (2015) found out with over-the-counter malaria prevention treatments in Kenya. Particular products such as LLINs also face cultural barriers to adoption (Monroe et al., 2014). This study therefore aims at expanding evidence on interventions for nudging preventive health uptake by looking at the role of CBHI uptake.

4.2.5 Effect of health insurance on preventive health outcomes

Studying the effect of health insurance on health outcomes requires the understanding of two issues. The first issue is that the primary role of health insurance is financial protection (Acharya et al., 2013; Cutler and Zeckhauser, 2000) and due to this, improvements in health that are as a result of consuming more care are conventionally taken as moral hazard (Ehrlich and Becker, 1972; Pauly, 1974). The second issue is that increasing health service utilisation is not always linked to moral hazard (Mendoza, 2016; Seog, 2012). It is therefore important to separate moral hazard from the desirable or beneficial insurance from service utilisation as a result of health insurance coverage.

Grignon (2014) provides a framework in which this separation can be made. He introduces the concepts of need and preference, where the need is not moral hazard whereas preference is. A situation would be inferred as a preference in consumption of health services only when an individual simply prefers to consume more health care because of the subsidised health costs or income effect from being insured (Nyman, 2001). For instance, teeth whitening or plastic beautification surgeries would fall into this category. A common moral hazard indicator in developing countries is a preference to use caesarean section delivery in non-emergency or without recommendation by a doctor, a phenomenon that has been observed in China (Long et al., 2012). On the other hand, Grignon (2014) suggests that needed care is the type which is clinically necessary to maintain health, for instance, routine dental check-up or other health screenings. Preventive health treatments strategies fall within needed care category rather than preferred care. In that case, when preventive health practices reduce the probability of illness, insurance can be complementary to both prevention and treatment (Barigozzi, 2004).

In this regard, there are a number of studies that analyse the effects of health insurance on different health outcomes in developing countries. While evidence is still lean, it is inconclusive. A majority of these studies are from Latin America. From Colombia, Giedion et al. (2010) found an 8 percentage point increase in child immunisation and 6 percentage point increase in antenatal visits for mothers enrolled in the subsidised insurance program for the poor. Giedion et al. (2010) also reported that contributory health insurance was associated with increasing preventive dental check-ups by 34.2 and 45.6 percentage points among the formally employed and self-employed households respectively. Still, in Colombia, Miller et al. (2013a) evaluated the effect of a publicly financed health insurance for the poor on use of preventive services among other outcomes and found that utilisation of a preventive physician visit increased by 29 percentage points while the number of growth monitoring assessments increased by 1.5 times more. Two other studies in Peru (Bitrán et al., 2010) and Costa Rica (Cercone et al., 2010), showed that insurance was however associated with improvement in the rate of full immunisation and growth monitoring.

Another set of studies from Mexico, following the 2003 health reforms also provide some inconclusive evidence. King et al. (2009) found that health insurance did not significantly influence the utilisation of preventive services but rather conclude that there might be some ex-ante moral hazard (reduced utilisation) regarding cancer and eye tests and flu vaccines. A similar inference is drawn by Spenkuch (2012) analysis. However, other studies particularly Pagan et al. (2007) and Rivera-Hernandez and Galarraga (2015) found that people with insurance, especially the poor, were more likely to use preventive services. It is, however, important to point out that early evaluations might not reveal behaviour change, which might take a longer to, change as Victora and Peters (2009) warned with respect to King et al. (2009)'s study.

Two studies in Ghana looked at the prevention of malaria through utilising LLINs (Yilma et al., 2012) and taking anti-malarial medication for children (Gajate-Garrido and Ahiadeke, 2015). After implementing a propensity score matching strategy, Yilma et al. (2012) found a reduction in the use of LLINs for insured households. However, in their analysis of malaria prevention for children, Gajate-Garrido and Ahiadeke (2015) found that being insured increased the possibility of children taking anti-malaria medicine by 25.2 percent and malaria-related child care seeking increased by 29.5 percent. In India, though Panda et al. (2015) found that households in insurance had a 5 percentage point advantage in knowledge of preventive practices, and a 6 percentage point advantage in practising preventive strategies for water, air, and vector-borne diseases. By and large, there is still a dearth of evidence on the effect of insurance on preventive health and it is hoped that this paper shades more light on the issue.

4.2.6 Our contribution to the literature

This study makes two contributions to literature. The first contribution is to provide lessons from evaluating a self-sustaining CBHI scheme that has been in operation for close to two decades. The time factor is important for development evaluations (Victora and Peters, 2009) because treatment effects might change as has been seen in the case of cooking stoves on mothers in India (Hanna et al., 2016). It has therefore been suggested that sufficient time for evaluating health intervention should be between 5 and 7 years (Bryce and Victora, 2005). Therefore, this study, undertaken roughly two decades after the scheme started, provides some indication of sustained behaviour change effects.

The second contribution that is unique to our study is the type of CBHI evaluated. The Kisiizi Hospital CBHI scheme is different from other CBHI schemes in two distinct ways. First, the scheme is solely community owned and financed and does not have any subsidisation from any government or non-government institution. This makes it unique in that schemes in other countries are subsidised by the government or donors and therefore the actual premiums are not fully paid by the insured individuals (Fenny et al., 2018; Kalk et al., 2010). The second distinction is associated with the central role played by burial groups. As opposed to individual household enrolment as in other schemes elsewhere, enrolment is based on membership in burial groups built on kin relationships. These burial groups have existed for possibly hundreds of years (Katabarwa et al., 1999) and are a central part of social lives of people in this region (Carswell, 2007; Edel, 1996). Moreover, these kin-associated groups have been found to be important pathways for preventive health interventions (Katabarwa et al., 2000a, 2004, 2010a). They, therefore, bring a rare and largely underutilised vehicle of community development and health promotion.

4.3 Theoretical and empirical strategy

4.3.1 A model of preventive health

Joining and remaining in insurance can be taken as an investment which has latent income returns in form of low direct cost of health services, in case of illness (Nyman, 2001). To theoretically elaborate on investments in preventive health, Dupas (2011b) developed a model of preventive health. In this model, health insurance is taken as an investment through which prevention can be increased. It is considered that a household maximises utility expressed in a function such as

$$\sum_{i=1}^{T} E_t \left(\frac{1}{1+\sigma}\right)^t U_t + B\left(A_{T+1}\right), \tag{4.1}$$

where σ is a discount rate, B is a bequest rate (a starting point value of wealth as suggested in Mitchell and Carson (1985)) and U_t (Utility) is given by

$$U_t = U\left(H_t, C_t, L_t\right), \tag{4.2}$$

Where H denotes the stock of health of a household, C is the consumption of other goods while L denotes leisure. The health stock is a commodity that households value and have a certain degree of control over. For instance, a household might decide to immunize their children, seek health care from any provider of choice or invest in any other preventive health technology. As Dupas (2011b) states, a household can make either preventive health investments, which reduce the susceptibility to a health shock or sickness or make remedial investments such as seeking tertiary care. If remedial health investments are not undertaken household health stock remains permanently diminished after a health shock. The household health stock evolves over time as follows:

$$H_t = H_{t-1} + \pi_t min\left(remedy_t - shock_t, 0\right), \tag{4.3}$$

Where π_t is the probability of an illness or other health shock is at a time ;̈$shock_t$ is the severity of the shock and $remedy_t$ measures the adequacy of the response to the shock (that is; how much the remedial investment mitigates the loss caused by the health shock). As Dupas further provides, the probability of the shock π_t is endogenous because it depends on the preventive investment being made up to time textitt-1 which can be denoted as $prevent_{t-1}$. It also depends on a random variable ϵ_t, which is independently and identically distributed for all t and captures the fact that the health shock is subject to randomly varying threats outside the household's control. For example, the likelihood of malaria might depend not only on the household's use of mosquito nets but also rainfall intensity. This can be formally presented as:

$$\pi_t = \pi\left(prevent_t, \epsilon_t\right). \tag{4.4}$$

This implies that the health shock will depend first on how much the household previously invested in preventive strategies and, second, on the adequacy of response to those shocks that did occur. If the response to the shock is inadequate ($remedy_t < shock_t$), then the health shock carried forward to the next period is reduced. Households have the following budget constraint:

$$p_c C_t + p_p prevent_t + remedy_t = w\left(\bar{T} - L_t\right) + rA_t + W_t, \tag{4.5}$$

Where the *p's* denote prices, w the wage, $\bar{T}$ the total time endowment and W represents the unearned income such as remittances. In this model, some of the health investments might be time investments, for instance, travelling to the health centre and waiting time, in which case, their price is the opportunity cost of time. At each period, after having observed whether a health shock has occurred and the unearned income, the households choose the levels of preventive investment, remedial investment, household consumption, and leisure to make. This model indicates that while preventive health investments in one period enter utility in the immediate future period, remedial (curative) health investments enter directly in the utility of the current period. This implies that preventive health investments decrease faster with the discount rate than remedial investments. As Dupas (2011b) submits, while this model is simplified, it, however, gives us a basis to understand the key determinants of households' health investment decisions. As discussed in the literature review above, some key issues that affect these decisions at the household level are the level of information, financial constraints. The literature discussed basically looks at these two broad issues - information access and financial constraints.

While the review by Dupas (2011b) review touches on the effect of social learning as a way in which information spreads in networks, the studies reviewed do not look at the effect of membership in a socially-controlling community organisation in which norms, practices, loyalty and expectation of mutual support are held in high regard. This is the addition we bring to this literature by studying the effect of membership in an organically formed community health insurance scheme.

4.3.2 Empirical strategy:Inverse probability weighting (IPW).

Estimating the average treatment effect of CBHI membership on preventive health, with cross-sectional data possess one main challenge of endogeneity of health insurance and health outcomes (Levy and Meltzer, 2008). Endogeneity might emanate from self-selection where random assignment is not possible for practical reasons as in this case study. In order to overcome this challenges, Inverse Probability Weighting (IPW) on the propensity score is applied. This method builds on propensity score matching methods introduced by Rosenbaum and Rubin (1984, 1983) and facilitates estimating of causal effects controlling for the observable determinants of selection in the treatment such that both the treated and control groups have the same probability of receiving the treatment. The control and treatment groups hence do not have any systematic differences in the observed covariates measured (Austin and Stuart, 2015; Imbens and Wooldridge, 2009). The analytical strategy used here follows Hirano and Imbens (2001) in applying IPW to acquire the average treatment estimates.

4.3.2.1 Selection on the observables and balancing diagnostics

An important step in reaching an efficient estimator is the choice of covariates to include in the treatment selection model. Some researchers consider each covariate based on its predictive power of the treatment, shown by the t-statistic (Cole and Hernán, 2008; Hirano and Imbens, 2001). This approach, however, might lead to omission of important variables which have substantive usefulness even when they do not have significant predictive power (Imbens and Rubin, 2015). Imbens and Rubin (2015, pp. 285-288) therefore advise on selecting the covariates significant treatment prediction and those with theoretical substantive usefulness. As a matter of principle, the selected covariates must minimise the mean squared error in order to achieve higher precision (Austin, 2011). Because this process involves a two-step procedure, robust standard errors were applied (Wooldridge, 2010, p. 934). In constructing the treatment selection model, a mild non-additivity (two two-way interaction terms) and non-linearity (one quadratic term) model, following Austin and Stuart (2017) was implemented.

For the inverse probability weighting to be efficient in estimation, the sample's estimated propensity score should fulfil the overlap assumption such that $0 < \epsilon(x) < 1$. In order to achieve a sufficient overlap, StataCorp (2015) treatment effects estimation strategy contains an inbuilt framework for checking violation of the overlap assumption[5]. The treatment selection model is sufficiently built in such a way that all the observations do not violate the overlap cut-offs and hence all observations are used.

Furthermore, covariates have to be balanced and present no significant differences across the treatment statuses conditioning on the propensity score (Austin, 2009). The standard measures for balancing in IPW are reporting the standardized means and variance ratios, checking for over identification and reporting the kernel density graphs for individual covariates (StataCorp, 2015, p. 156). Covariate balancing results are reported in the supplementary tables in the Annex C. For over-identification tests based on Imai and Ratkovic (2014), the model provides a Hansen's J-statistic was 4.926 *(p-value* = 1.000) with 32 degrees of freedom, indicating that we do not have sufficient evidence to reject the hypothesis that all the covariates are balanced. Guo and Fraser (2015) suggested another method suitable for ascertaining balance of the covariates in IPW by implementing weighted simple regressions of the covariates on the treatment while weighting by the IPW. The sample is well balanced if the weighted coefficients of the covariates are not significantly associated with the treatment, indicating that weighting removes all imbalances. This strategy is undertaken and results also reported in Annex C.

4.3.3 Treatment and outcomes

Treatment: The treatment variable for this study is membership in CBHI, recorded as a dummy for 1 if a current member of the Kisiizi CBHI scheme and 0 otherwise. **Outcomes:** The study was interested in seven preventive health strategies. These were:

1. Use of LLIN for all household members - was assessed as true if all the household members slept under an LLIN. The interviewer also observed the place of sleeping to ascertain if the LLIN was hanged or a hanging hook was present.
2. Household level treatment of water for drinking and other uses. The measure of water treatment in this study was based self-reported use of sedimentation, filtration or chemical disinfection as methods of water treatment as classified by the World Health Organisation (WHO, 2013b).

[5]The inbuilt overlap tolerance level corresponds to probability of treatment higher than 0.00001 and less than 1-0.00001. Observations with a probability of treatment lower or higher than default tolerance are omitted from analysis

3. Handwashing - was assessed by observation if the household had a hand washing facility at the latrine. If the household had an indoor toilet, handwashing was also recorded as true.
4. Vitamin A supplementation - was assessed as true if a child had received a vitamin A supplement in six months prior to the survey.
5. Iron supplementation - was assessed true if the child had received an iron supplement 7 days prior to the survey,
6. Child deworming - was assessed as true if the child had received deworming tablet in six months prior to the survey, and
7. PCV vaccination - was assessed as true if a child had ever received the PCV vaccination.

4.4 Results

4.4.1 Descriptive results

Twenty-eight base variables were included in the predictive model of CBHI participation. Table 23 details the summary statistics of these base variables, the treatment and all the outcomes. 43.8 percent of the respondents were enrolled in CBHI and the mean age of the children in the sample was 30.2 months. Slightly over 55 percent of the children were born in a health facility. 48 percent of the children were male. The mean age of the mothers was 30.2 years. Mother's and father's education were merged into one indicator of parental education where we assign 1 if one of the parents had attended some secondary level education and 0 otherwise. 30.4 percent of the households had at least one parent with some secondary level education. Slightly more than half of all the respondents identified as Catholics.

Following Vyas and Kumaranayake (2006), Principal Components Analysis (PCA) is implemented to construct four continuous variables that rank households. The variables are a wealth index for socioeconomic welfare levels, perception index for perceptions on health insurance that follows Jehu-Appiah et al. (2012) and a social connectivity index that measures access to information and connection to leaders and involvement in lending and borrowing from village members. The fourth is leader and social influence, which measures the extent to which households felt they were influenced by local social leaders (such as burial group leaders, village opinion leaders and the like) and other social contacts to join CBHI. The wealth index was constructed in two levels. First indices for household living conditions, household durable asset holding, access to water and sanitation facilities and agriculture endowments of land and livestock were constructed. The numbers of livestock are converted to equivalent scales using total livestock conversion units (Harvest Choice, 2011)[6]. The four indices were further reduced through a second level PCA proce-

[6] The livestock conversion factors are: cattle = 0.7, sheep = 0.1, goats = 0.1, pigs = 0.2, chicken = 0.01

dure to attain the overall wealth index. The perception index was constructed from 34 Likert Scale statements whose responses ranged from 1 for completely disagree to 5 for completely agree. Perceptions on six dimensions, namely; financial protection, the convenience of insurance, management of the insurance scheme, premiums paid, quality of health care, and health beliefs, are generated. These are further reduced to one single perceptions index through a second level PCA procedure. The variable for social and leader influence from kinsmen and community leaders was developed using a similar strategy.

The average household had about 6 members. Close to 70 percent of the households in the study knew that at least one in four of the immediate neighbours participated in CBHI and 53 percent knew actual annual premiums. The average waiting time at a health facility was close to 1.5 hours. In 35 percent of the households, husbands were in casual employment while in only 10 percent, wives were casual employment status. 52.8 percent of the mothers had had this kind of interface with a TBA.

All households belonged to a burial group. Burial group size ranged from 18 to 200 households with the average burial group having 72 households. On average, each village had about 6 burial groups. Dummies for village economic activity were included. These were either predominantly pastoralism or predominant banana cultivation. 19 percent of the respondents were in villages which were predominantly livestock villages and about 26 percent were in predominantly banana cultivating villages. The average distance from a village to the nearest health centre was 4 kilometres.[7] Dummies for the health centre and school were also included showing that 40 percent of the respondents were from villages with a health centre and 63 percent from a village with a school.

For the outcomes of focus, 44.2 percent of the households reported sleeping under an LLIN. Water was classified as treated if a respondent reported using chlorine or boiling the drinking water for the household; this was reported in 53 percent of the households. However, only 12 percent of the households had a handwashing facility at their toilets. Among the under-five children studied, Vitamin A supplementation was reported for 77.2 percent, deworming for 74.1 percent, and iron supplementation for only 10.1 percent. 30.2 percent of the children had received PCV vaccination.

4.4.2 Empirical results

IPW produces robust causal effects provided that propensity score model is correctly modelled (Austin, 2011; Austin and Stuart, 2015). To check for model specification, the treatment models had a Pearson's chi-square goodness of fit p-value of 0.628 and a mean VIF of 8.7. The Link Test and classification test also indicate that the model was well specified. Results of the logistic model for treatment prediction, elaborating on the odds ratios of the variables that significantly predict the probability of treatment assignment are presented first.

In terms of variables that positively influence the probability of CBHI participation, it was found that a higher household's socioeconomic status was associated

[7]Distance to health facility was measured in kilometres on a motor vehicle usable road.

Table 4.1: Descriptive results of the variables used in the analysis

VARIABLES	Man	Min	Max	S
CBHI Participation	0.438	0	1	0.497
Number of years in CBHI	5.103	1	11	3.056
Child's age (months)	30.202	5.550	60.580	15.152
Mother's age (years)	30.204	14.010	56.540	7.164
Birthweight	3.186	2.00	5.60	0.529
Child is male	0.481	0	1	0.500
Parental secondary education	0.304	0	1	0.460
Health facility delivery	0.554	0	1	0.498
Catholic	0.504	0	1	0.501
Wealth index	8.94×10^{-10}	-1.754	8.365	1.344
Neighbour in CBHI	0.692	0	1	0.462
Husband employment- casual	0.351	0	1	0.478
Wife employment- casual	0.101	0	1	0.302
Household diet diversity score	4.080	0	8	1.280
Burial group size	71.366	18	200	26.054
Number of burial group in village	5.601	1	10	3.349
Satisfaction with health workers	0.851	0	1	0.356
Perception index	-6.19×10^{-09}	-2.036	1.248	0.509
Social and leader influence	-6.79×10^{-09}	-5.006	2.014	1.506
Access to Information	-2.20×10^{-09}	-2.631	4.472	1.289
Interface with TBA	0.528	0	1	0.500
Knows premium	0.528	0	1	0.500
Waiting time (mins)	88.621	5	540	108.851
Village has TBA	0.752	0	1	0.432
Village has health centre	0.401	0	1	0.491
Village has school	0.634	0	1	0.482
Village economic activity - banana	0.261	0	1	0.440
Village economic activity - pastoralism	0.192	0	1	0.394
Distance to nearest health facility (kms)	4.001	0	11.500	2.919
Outcomes				
Used LLIN	0.442	0	1	0.497
Household water treatment	0.528	0	1	0.499
Hand-washing facility	0.120	0	1	0.313
Vitamin A supplement	0.772	0	1	0.420
De-worming	0.741	0	1	0.438
Iron supplement	0.101	0	1	0.302
PCV vaccine	0.302	0	1	0.460
N			464	

with increased odds of participation by almost twice (OR 1.988; 95% CI 1.288 - 3.068). However, the odds of participation reduced as socioeconomic status improved shown by the quadratic term of wealth index. Belonging to the Catholic faith was associated with increasing the odds of participation by more than twice the enrolment of non-Catholics (OR 2.229; 95% CI 1.077 - 4.612). While mothers' casual employment had a negative association on CBHI participation, it was found that fathers'/ husbands' casual employment increased odds of participation by over 2.4 times (OR 2.346; 95% CI 1.034 - 5.324). In addition, households who were satisfied with health workers conduct had odds of enrolment almost 4 times higher (OR 3.936; 95% CI 1.416 - 10.944). A percentage change in the number of burial groups in the village was associated with increasing the odds of participating in CBHI almost twice (OR 2.053; 95% CI 0.945 - 4.459). Households that expressed social and leader influence were also more likely to enrol (OR 1.404; 95% CI 1.037 - 1.902) and so did households with better access to information (OR 1.407; 95% 0.994 - 1.991). Households who lived further from health centres had a slight advantage in enrolment (OR 1.191; 95% CI 0.971 - 1.460). Finally, it was found that knowing the actual annual premiums required to for CBHI participation was associated with increasing the odds of participation by over 20 times more (OR 22.670; 95% CI 10.595 - 48.509).

On the variables that negatively influence the probability of CBHI participation, child's age, employment type of the woman, size of the burial group a household belonged to, and belonging to predominantly pastoralist villages, were prominent. It was found that an increase in child's age by one month was associated with a reduction in odds of a households' participation by 2.3 percent (OR 0.977; 95% CI 0.953 - 1.002). Households in which the respondent mother was a casual labourer were less likely to participate in CBHI with odds of participation reduced by close to 64 percent (OR 0.361; 95% CI 0.115 - 1.131). A one percent increase in the size of the burial group a household belong to was associated with reducing odds of participation by 77 percent (OR 0.229; 95% CI 0.089 - 0.587). Households in villages which had a traditional birth attendant were less likely to enrol in CBHI with odds reduced by over 73 percent (OR 0.296; 95% CI 0.087 - 1.001). Finally, households residing in villages whose main economic activity was pastoralism had odds of participation reduced by over 90 percent (OR 0.095; 95% CI 0.017 - 0.544).

4.4.2.1 Average Treatment Effect of Insurance

First, the average treatment effect results are presented. It is found that household insurance had a positive effect on all but only one outcome, the PCV vaccination. Table 25 below presents the results of all the seven outcomes of interest. The outcomes can be categorized into two ways; (1) home-based preventive health practices and (2) facility-based preventive health interventions. First, the ATEs on the home-based preventive health practices, namely: use of LLIN, water treatment, and handwashing are examined. These are shown in models 1, 2 and 3.

Table 4.2: Logistic model for CBHI participation

Variables	CBHI Participation		
	OsRatios	Std Error	99% Conf. Intervals
Child's age	0.977*	(0.012)	0.953 - 1.002
Mother's age	1.031	(0.035)	0.965 - 1.101
Child is male	0.684	(0.249)	0.335 - 1.397
Log Birthweight	1.247	(0.414)	0.651 - 2.388
Parental secondary education	0.485	(0.219)	0.200 - 1.173
Health facility delivery	1.340	(0.498)	0.647 - 2.778
Catholic	2.229**	(0.827)	1.077 - 4.612
Wealth index	1.988***	(0.440)	1.288 - 3.068
Wealth index squared	0.863***	(0.040)	0.788 - 0.945
Neighbour in CBHI	2.093	(0.990)	0.828 - 5.290
Husband employment - casual	2.346**	(0.981)	1.034 - 5.324
Wife employment - casual	0.361*	(0.210)	0.115 - 1.131
Household diet diversity score	0.880	(0.126)	0.665 - 1.164
Household size	0.930	(0.097)	0.758 - 1.141
Log burial group size	0.229***	(0.110)	0.089 - 0.587
Log number of burial groups in village	2.053*	(0.813)	0.945 - 4.459
Satisfaction with health workers	3.936***	(2.054)	1.416 - 10.944
Perception index	0.161	(0.185)	0.017 - 1.530
Satisfaction*Perception index	4.144	(4.835)	0.421 - 40.792
Social & Leader influence	1.409**	(0.220)	1.038 - 1.912
Access to information	1.407*	(0.249)	0.994 - 1.991
Interface with TBA	0.578	(0.247)	0.251 - 1.336
Interface with TBA*access to information	1.030	(0.299)	0.583 - 1.820
Know premiums	22.670***	(8.799)	10.595 - 48.509
Waiting time	1.001	(0.001)	0.998 - 1.003
Village has a TBA	0.296*	(0.184)	0.087 - 1.001
Village has a health centre	0.653	(0.494)	0.148 - 2.874
Village has a school	0.980	(0.660)	0.262 - 3.665
Village economic activity - banana	0.356	(0.229)	0.101 - 1.254
Village economic activity - pastoralism	0.095***	(0.085)	0.017 - 0.544
Distance to nearest health centre	1.191*	(0.124)	0.971 - 1.460
Constant	37.155	(104.625)	0.149 - 9266.190
Goodness of fit (Pearson chi square)		0.629	
Mean VIF		8.73	
Link test (Hat squared)	−0.060	(0.041)	-
Pseudo R-squared		0.586	
Observations		464	

Robust standard errors in parentheses
Significance levels ***p<0.01, **p<0.05, *p<0.1

Table 4.3: Average treatment effects of CBHI participation (ATE)

Treatment	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A	(5) Iron	(6) Deworming	(7) PCV
CBHI participation	0.285***	0.200**	0.062	0.160	0.131**	0.234**	0.032
	(0.084)	(0.096)	(0.060)	(0.113)	(0.060)	(0.103)	(0.061)
PO (No CBHI)	0.274***	0.444***	0.066**	0.627***	0.060***	0.591***	0.217***
	(0.064)	(0.088)	(0.017)	(0.110)	(0.018)	(0.099)	(0.044)
N	464	464	464	464	464	464	464

Robust standard errors in parentheses
Significance levels ***p<0.01, **p<0.05, *p<0.1

Results indicate that compared to households without insurance, the probability of using LLIN for households with insurance increased by 28.5 percentage points, higher than the potential outcomes of 27.4 percent usage of LLIN in the absence of CBHI. CBHI participation increased the probability of water treatment by 20 percentage points above the water treatment rate of 44.4 percent for households without CBHI. A positive effect of CBHI on handwashing corresponding with a 6.2 percentage point increase was also observed though not statistically significant.

The ATEs for facility-based preventive health interventions are then examined. These were vitamin A supplementation, Iron supplementation, deworming, and PCV vaccination. Positive effects were found on all four of them, with significant effects identified on iron supplementation and child deworming. In particular, it was found that CBHI participation increased the probability of taking iron supplements by 13.1 percentage points above the potential outcome of only 6 percent in non-CBHI households. The largest impact of clinical-related outcomes is observed in deworming. The analysis indicates that the probability of child deworming increased by 23.4 percentage points once a childŠs household joined CBHI above the without CBHI deworming level of 59.1 percent. ATEs for vitamin A supplementation and PCV vaccine, though positive were not statistically significant.

The above results can be also be intuitively presented as a proportion of the potential outcome (no CBHI) that CBHI induces. In other words, the ratio of the ATE to the control level potential outcomes. In order to establish this, the ATE is examined as a proportion of potential outcomes. These results of the point estimates and associated delta robust standard errors are presented in Table 23 below. First, it is observed that all the measured preventive health treatments have a positive difference between the potential outcomes and average treatment effects indicating that CBHI had a positive effect on all them. We look at each outcome in detail below.

Use of LLIN: The study findings indicate that the probability of using LLINs more than doubles (increases by 104 percent), once a household adopts insurance in the area of study. Generally, south-western Uganda has a low malaria prevalence. Epidemiological studies have found that in very high altitude areas like south-western Uganda, malaria prevalence was the lowest in the country (Yeka et al., 2012). These

Table 4.4: ATE as a proportion of potential outcomes

Outcome	Cof	Std. Err.	95% Conf. Interval
LLIN	1.039**	0.503	0.053 - 2.025
Water Treatment	0.450	0.297	−0.133 - 1.032
Handwashing	0.939	1.004	−1.029 - 2.907
Vitamin A	0.256	0.223	−0.182 - 0.694
Iron supplement	2.175*	1.296	−0.365 - 4.714
Deworming	0.397*	0.239	−0.071 - 0.865
PCV	0.148	0.306	−0.453 - 0.748

Robust standard errors in parentheses.
Significance levels ***p<0.01, **p<0.05, *p<0.1

results are supported the recent Malaria Indicator Survey that found that 98 percent of the households in the south-western region had an LLIN and only 13.5 percent of the respondents from the region reported a fever (UBOS and ICF International, 2015). While summary results indicated two important things. There were no significant differences in LLIN ownership among treated and control households. However, 55.2 percent of treated households reported all household members sleeping under an LLIN compared to 35.6 percent in control households. Similarly, child fever prevalence in treated households was only 7.9 percent compared to 14.9 percent in control households. These results can, therefore, be interpreted as a behaviour change effect in the use of LLIN associated with CBHI participation. These results can be compared with previous studies in East Africa. Studies using price instruments to understand the adoption and use of LLINs in Kenya have found that any upward change in price led to steep drops in adoption rates. However, LLINs have now been adopted to almost near-universal levels. Perhaps the most important question, therefore, is not whether households can own an LLIN but whether they can consistently use one. By asking and ascertaining whether all members of a household slept under an LLIN, this analysis goes beyond only ownership to usage. These results, therefore, indicate the participating in CBHI can be one of the avenues through which changing behaviour towards increased LLIN use can happen.

Household water treatment: The study finds that without CBHI, the probability of a household to practice some form of water treatment was only 44.4 percent and with CBHI participation, this probability increased by 20 percentage points, a 45 percent increase over the no-CBHI participation probability. Water treatment is important for preventing diarrhoeal diseases which account for a large proportion the disease burden in many developing countries. Only 52.8 percent of the respondents reported treating water. Though the survey average was lower than the national average of 72.8 percent in 2011 (UBOS and ICF International, 2012), households in CBHI had a higher water treatment prevalence of 57.6 percent compared to those with no CBHI at 49.0 percent. It is important that rural households have access to clean water or access to technologies for water purification. A number of studies are premised on the fact that availability and uptake of water treatment technologies in developing countries is low.[8] Moreover, having the technology for water treatment and actually treating the water are not usually consistent as studies in Kenya have found (Luoto et al., 2014). These results indicate that even without costly water treatment interventions, it is possible to nudge behaviour when households join CBHI.

Handwashing behaviour: After controlling for selection into CBHI, it was found that potential outcome for the probability of handwashing was 6.6 percent. However, with CBHI, the probability of having a handwashing facility by a household's latrine increased by 6.2 percentage points, almost doubling this probability (94 percent from the potential outcomes). While this result was not statistically significant, it should be important policy-wise. Generally, handwashing is low in Uganda. Only 29 percent of surveyed households in 2011 had a handwashing facility and this was even lower at 20 percent in the south-western region (UBOS and ICF International, 2012). For this survey, it was even much lower at 11.0 percent. Doubling this probability was therefore profound. Like water treatment, handwashing is very important in the promotion of child health (Luby et al., 2004, 2005) therefore even with no statistical significance, any effort that considerably improves this behaviour is important for policy.

Vitamin A supplementation: 38 percent of children between 6 and 59 months had vitamin A deficiency in 2011 (UBOS and ICF International, 2012). One of the ways of improving vitamin A intake is through the integrated child health days, a month-long activity held twice a year, in May and November (Fiedler and Semakula, 2014). The main services provided are vitamin A supplementation, deworming and immunisation for both catch-up immunisation and booster doses. It is therefore expected that a child below the age of five should receive vitamin A supplementation at least once every six months. The survey question for this study, consistent with other health surveys like the DHS asked whether a child had taken a vitamin A supplement at least once in six months prior to the survey. On average, 77.2 percent of the children had received a Vitamin A supplementation, which was significantly higher than the national average of 56.8 percent and the south-western average of 44.1 percent in the 2011 DHS (UBOS and ICF International, 2012). The study results indicate that without CBHI, the probability of receiving a vitamin A supplement was 62.7 percent, however, with CBHI participation, Vitamin A supplementation increases 16 percentage points equivalent to a 25.6 percent increase. Like handwashing, this result was not statistically significant.

Iron supplementation: Iron supplementation is important for anaemic children. Close to half of all under-five children in Uganda were anaemic in 2011 (UBOS and ICF International, 2012). Although child anaemia has multiple causes, about half of anaemia cases are associated with iron deficiency (Asobayire et al., 2001). It is therefore recommended that iron supplements are taken on a daily basis (WHO,

[8] See for instance studies cited by Dupas (2011b) and more recently on factors for uptake of water filters in Bangladesh (Luoto et al., 2012, 2014; Najnin et al., 2015), effect of information on adoption decisions in Indian (Jalan and Somanathan, 2008) and Bangladesh (Madajewicz et al., 2007) and more recently, effect on incentivising households for uptake with vouchers in Kenya (Dupas et al., 2016) and with microloans in Cambodia and India (Blanton et al., 2014) respectively.

2013a). Standard surveys usually ask about iron supplementation in seven days prior to the survey. This survey findings that only 6 percent of the children had received iron supplements was in line with the 7 percent from the 2011 DHS nationwide survey. An ATE of 13.1 percentage points over the 6 percent potential outcome indicated that CBHI participation could more than double intake of iron supplements.

Deworming: Deworming is an essential component of the integrated child health days programme in Uganda. Children are expected to receive preventive deworming chemotherapy at least twice a year. Like in the case for vitamin A supplementation, a large proportion of respondents, 74 percent, had received deworming chemotherapy. The potential outcome without CBHI was 59.1 percent. With CBHI, the probability of receiving deworming chemotherapy was higher by 23.4 percentage points, representing a 39.7 percent effect.

Pneumococcal Conjugate Vaccine (PCV): The last outcome we measure is on receiving PCV. Uganda introduced the PCV, a vaccine for childhood pneumonia in 2013 (WHO, 2014) and is currently in scale-up to all health facilities across the country. There is no study so far that looks into issues that could affect uptake of this new vaccine. This study, therefore, provided an opportunity to study the effect of CBHI on its uptake having established that the vaccine was offered at the health facilities in our study area. Overall, receiving the vaccine was found to be still considerably low compared to other routine vaccines with only 30.2 percent of the children receiving it. Results indicated that CBHI participation increased the probability of receiving the vaccine by 14.8 percent, an increment of 3.2 percentage points over the potential outcomes of 21.7 percent. Though not statistically significant for the whole population, this finding also indicated that CBHI could have important contributions in the uptake of new child health interventions such as PCV.

The analysis of the difference between potential outcomes and average treatment effects helps to clearly quantify the extent of the change in the situation where a household does participate in CBHI. While the differences regarding water treatment, handwashing, vitamin A supplementation, deworming and PCV were not statistically significant, they were strongly positive and should be very relevant for policymakers.

4.4.2.2 Average Treatment Effect on the Treated

A more precise estimate of the effect of CBHI is the Average Treatment Effect on the Treated (ATET) which measures the effect of CBHI participation on enrolled households by comparing them with their counterfactual outcome had they not been treated (Cerulli, 2014; StataCorp, 2015). A number of changes are observed once inference is drawn on only households that participate in CBHI. Within the CBHI participating households, CBHI had a positive effect on all the seven outcomes measured and a statistically significant effect on five. The probability of using

Table 4.5: Average treatment effects of CBHI participation (ATET)

Treatment	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A supplement	(5) Iron supplement	(6) Deworming	(7) PCV
CBHI participation	0.352***	0.175	0.080***	0.28	0.083***	0.299*	0.157**
	(0.110)	(0.161)	(0.024)	(0.175)	(0.028)	(0.158)	(0.065)
PO (No CBHI)	0.200*	0.401***	0.018	0.503***	0.035*	0.479***	0.128**
	(0.104)	(0.156)	(0.012)	(0.176)	(0.021)	(0.156)	(0.054)
N	464	464	464	464	464	464	464

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

LLINs increased by 35 percentage points over a potential outcome probability of 20 percent had the insured households not insured. The probability of acquiring a handwashing facility increased by 8 percentage points over a potential outcome of only 2 percent and the probability of water treatment was also positive.

In terms of clinical preventive interventions, statistically significant effects were found regarding iron supplementation, deworming and PCV. The probability of iron supplementation increased by 8.3 percentage points over a potential outcome of 3.5 percent and that of deworming chemotherapy, increased by 30 percentage points over a potential outcome of 47.9 percent. Similarly, the probability of receiving the new PCV vaccine increased by 15.7 percentage points over the potential outcome of 12.8 percent.

4.4.3 Robustness Checks

4.4.3.1 Weighted Least Squares regressions

The fact that all the seven outcomes are measured from the same treatment model, provides internal robustness. In this way, the variables included in the treatment selection model are not selected to influence one single outcome but rather for their overall predictive power and usefulness in determining treatment assignment. As a comparison to the IPW framework used (StataCorp, 2015, p. 239), a number of alternative weighting estimation strategies are proposed to test if they arrive at the similar or closely comparable results. The first one is a two-stage weighted least squares (WLS) regression where the weights are estimated from the first stage treatment selection equation. After the estimation of this WLS strategy, results indicate that coefficient estimates are essentially similar and only different in the standard errors. This is because the weights are generated from separate treatment selection and outcome regressions. Cerulli (2014) suggests that the strategy preferred (StataCorp, 2015), where the treatment and outcome regressions are estimated in an integrated process, is more efficient. These results are available in the Appendix

Table A.6. Two other weighting strategies can be used to check the stability of these results.

4.4.3.2 Nichols (2008) Weighting Strategy

Nichols (2008) provides a set of weights that develop an estimator building on Brunell and DiNardo (2004), where the weight of the treated observations is multiplied by the mean of treatment, such that the weight of treated observations is given as

$$\omega(W_{T=1}) = \frac{\frac{1}{\hat{\epsilon}(\chi)} * \bar{\chi}}{1 - \bar{\chi}}, \tag{4.6}$$

and the weight of the control observations is given as

$$\omega(W_{T=0}) = \frac{1}{1 - \hat{\epsilon}(\chi)}, \tag{4.7}$$

Table 4.6: Robustness check using Nichols (2008) re-weighting scheme

	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A supplement	(5) Iron supplement	(6) Deworming	(7) PCV
CBHI participation	0.285***	0.200*	0.062	0.160	0.131**	0.234**	0.032
	(0.092)	(0.106)	(0.056)	(0.123)	(0.064)	(0.117)	(0.066)
PO (No CBHI)	0.274***	0.444***	0.066**	0.627***	0.060***	0.591***	0.217***
	(0.064)	(0.093)	(0.018)	(0.116)	(0.019)	(0.112)	(0.050)
R Squared	0.0767	0.0349	0.2709	0.0259	0.0409	0.0542	0.0013
N	464	464	464	464	464	464	464

Robust standard errors in parentheses
Significance levels *** p<0.01, ** p<0.05, * p<0.1

Using Nichols (2008) weighting strategy, we find similar point estimates as our primary strategy. Moreover, these results are identical to the WLS results and hence our results are robust to a different weighting strategy.

4.4.3.3 Harder et al. (2010) weight stabilisation and trimming

As has been elsewhere in health research, IPW can be less sensitive to extreme weights which are generated in the presence of rare treatments (Austin and Stuart, 2017). Extreme weights might, therefore, bias the results. One of the options to deal with the possible effect of extreme weights is trimming, truncating or applying restrictions on functional maximum and minimum weight cut-offs (Austin and Stuart, 2017; Cole and Hernán, 2008; Lee et al., 2011). In a situation where extreme weights are thought to be present, Harder et al. (2010) propose a weight stabilisation procedure. The stabilisation of weights is achieved by separately multiplying the treatment and control with a constant term equal to the expected value of treatment and control respectively. Stabilisation, therefore, reduces the variability of the IPW weights and reduces the variance in the treatment effects estimates. The stabilised weights are then given as

$$\frac{\sum_{i=1}^{N_T} PS_i}{N_T} * \frac{1}{PS_i} \tag{4.8}$$

And when the observation is in the controls,

$$\frac{\sum_{i=1}^{N_C} (1 - PS_j)}{N_C} * \frac{1}{(1 - PS_j)}, \tag{4.9}$$

PS stands for the predicted propensity score while N_T and N_C stand for the number of treated and number of controls respectively. To achieve more precision, Harder et al. (2010) further suggest the implementation of a trimming strategy to remove the effect of a few remaining extreme weighted observations. Following their strategy, weights are trimmed to a maximum of 10 if the stabilised weight was larger than 10. These stabilised weights are then implemented on WLS regressions and results are detailed in Table 29 below. Since the stabilised and trimmed weights are different from those used in StataCorp (2015) *teffects ipw* estimation strategy and so the results are expected to differ, it is expected that outcomes significance and direction should remain as in the primary model.

Using these stabilised weights, statistically significant ATEs are found regarding use of LLINs, water treatment and iron supplementation and deworming, as in the case with the main model. The point estimates are however smaller as expected due to weight trimming. By and large, these results provide confidence in the primary model that even with using a different set of weights, CBHI had significant effects on at least four of the seven preventive health strategies measured and that this effect if not as much driven by extreme weights.

Table 4.7: ATEs from Harder et al. (2010) Stabilised and Trimmed Weights

	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A	(5) Iron	(6) Deworming	(7) PCV
CBHI participation	0.251***	0.130**	0.033	0.053	0.109**	0.134***	-0.007
	(0.064)	(0.065)	(0.043)	(0.060)	(0.055)	(0.058)	(0.055)
Constant	0.329***	0.487***	0.084***	0.718***	0.077***	0.678***	0.275***
	(0.043)	(0.048)	(0.017)	(0.045)	(0.020)	(0.047)	(0.039)
R Squared	0.0622	0.0164	0.0030	0.0035	0.0269	0.0222	0.0001
N	464	464	464	464	464	464	464

Robust standard errors in parentheses
Significance levels *** p<0.01, ** p<0.05, * p<0.1

4.4.4 Pathways of Impact

Having established that there is a largely positive and significant effect of CBHI on the utilisation of preventive health services, one outstanding question is to know how these effects come about, that is, understanding the pathways of impact. Two main pathways through which these effects are generated are suggested.

The intensity of CBHI and information diffusion: The first pathway of impact is through the intensity of CBHI which can be expounded on in two dimensions. The first one is the length of time households have participated in CBHI. Evidence from other development economics interventions suggests that the length of time of exposure to a treatment has considerable effects on the effectiveness of the intervention. For instance, while understanding the determinants of increasing retirement savings among American households, Beshears et al. (2013) found that the length of time coupled with simple timely reminders increased savings contributions in a retirements scheme considerably. Behrman et al. (2004) found significant effects on cognitive and psychosocial outcomes on Bolivian preschool children who were exposed to a preschool program for seven months or more compared to those exposed the program for at least one month. Time effects have also been found to be central to energy-saving behaviour change studies in developed countriesAllcott and Rogers (2012, 2014), finding that households which had a longer exposure to information reduced their energy use rates compared to households that received this information for only a shorter period even after the intervention had closed.

While this literature relates to individual effects it is plausible that the same mechanisms of treatment intensity also work in groups such as burial groups. In particular, after longer exposure to an intervention, there are possible peer effects which generate adherence, cooperation and reciprocal behaviour in such a manner that individual members do not want to be seen as diverging from an emerging behaviour or norm. This is the kind of cooperation that is revealed in energy conservation studies among households (Yoeli et al., 2013) and students (Delmas and Lessem, 2014). In this case study, the intensity of CBHI is in form of years of participation.

To test if this pathway is plausible, the treatment variable is changed from a dummy of CBHI membership to a multi-value treatment variable where some households are less intensively treated (1-4 years of participation), others are more intensively treated (5 or more years of CBHI participation) and the rest are a control group of those who did not participate in CBHI. In the collected data, 20 percent of the households are in the less intensive treatment and 23.5 percent are in the more intensive treatment while the remaining 58 percent were in control. In this framework, households in the more intensive treatment were expected to have a higher effect size than those in less intensive treatment. If there were significant effects in both treatments, the difference in effect sizes could then be studied to establish if the effect size in the more intensive treatment is significantly different from the effect size in the less intensive treatment. A multi-valued treatment effects model, with a logistic additivity and linearity treatment selection model (Austin Stuart, 2017) was then implemented. These results are shown in Tables 28 below, indicating the ATEs and Table 29 for the ATETs.

Table 4.8: Multi-value treatment effects of CBHI participation (ATE)

Treatment	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A Supplement	(5) Iron Supplement	(6) Deworming	(7) PCV
1-4 years	0.345***	0.261***	-0.057***	0.042	0.179**	0.151	0.022
	(0.087)	(0.080)	(0.019)	(0.109)	(0.080)	(0.099)	(0.054)
> 5 years	0.205***	0.052	0.036	0.017	0.027	0.143*	0.063
	(0.078)	(0.084)	(0.033)	(0.090)	(0.031)	(0.082)	(0.059)
PO (No CBHI)	0.315***	0.481***	0.074***	0.695***	0.062***	0.625***	0.193***
	(0.064)	(0.067)	(0.016)	(0.076)	(0.015)	(0.070)	(0.030)
N	464	464	464	464	464	464	464

Robust standard errors in parentheses
Significance levels p<0.01, ** p<0.05, * p<0.1

Two things can be inferred from the ATEs. There are significant effects in five of the seven outcomes. However, in the outcomes where the more intensive margin had a larger coefficient (hand washing and PCV), the point estimates were not significant. This might imply that the time effect was not present. In other words, going by the ATEs, it is possible that there are other reasons why we see these effects other than the length of time a household has participated in CBHI. However, a peculiar effect was found regarding hand washing in that a less intensive CBHI participation was associated with reducing the probability of having handwashing facilities by 6 percentage points while households in the more intensive CBHI participation had a visibly higher probability of handwashing though not significant. This might, therefore, suggest that the time effect is possible even when not statistically significant.

Regarding the ATET results in Table 29 below, the story is, by and large, the same, that the length of time in CBHI does not seem to have a strong effect on the results except for hand washing. For hand washing, it is observed that households in the more intensive treatment indeed increased their probability of hand washing more than those in the less intensive treatment. This, therefore, suggests while the time effect is not strong and conclusive, it might be fully ruled out.

Table 4.9: Multi-value treatment effects of CBHI participation (ATET)

Treatment	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A Supplement	(5) Iron Supplement	(6) Deworming	(7) PCV
1-4 years	0.311***	0.254*	0.0250	0.206	0.094**	0.291**	0.269***
	(0.120)	(0.130)	(0.022)	(0.151)	(0.039)	(0.126)	(0.063)
> 5 years	0.230*	0.164	0.099**	0.116	0.004	0.220	0.141*
	(0.132)	(0.146)	(0.044)	(0.162)	(0.026)	(0.135)	(0.079)
PO (No CBHI)	0.275**	0.413***	0.014	0.552***	0.032	0.433***	0.088**
	(0.109)	(0.125)	(0.009)	(0.152)	(0.021)	(0.120)	(0.035)
N	464	464	464	464	464	464	464

Robust standard errors in parentheses
Significance levels p<0.01, ** p<0.05, * p<0.1

These results indicate two things. The first one is that while the length of time a household participates in CBHI matters on how much it adopts preventive treatments, the effects of CBHI are not sustained by longer participation but instead attenuate over time. Secondly, related to the first issue, is a possibility of moral hazard. A conventional expectation regarding the time effect would be that the more intensive a household participated the higher the probability would be to adopt a preventive health treatment. However, as it is observed, this is not the case. It is probable that as people spend more years in CBHI, there might be a tendency to reduce health improving behaviours. Moreover, households with more intensive CBHI participation were also richer (with a more positive wealth index score) than the rest[9] . The ATET finding on handwashing, however, helps not completely rule out the participation length (time effect), indicating that learning and behaviour change were possible across time.

Another time and information pathway that is envisaged regards information flow and diffusion. This is expected to actualise through the frequency of group meetings which facilitate more information diffusion. Burial groups which have higher meetings turnover and higher group member's contact are expected to have higher information diffusion. Burial groups participating in CBHI met on average 14 percent per month more than those not participating in CBHI (2.36 times versus 2.07 times). Studies in Zambia (MacIntyre et al., 2012) and Nigeria (Kilian et al., 2016) regarding uptake of mosquito nets have shown that intensive exposure of households to information regarding uptake highly influences their probability of uptake. Insurance experience in this case study somehow mirrors these two dimensions of intensity-related impact pathway.

[9]This might imply possibilities of income gain in line with John Nyman's theory of demand of health insurance (Nyman, 2001, 2008)

Information diffusion and behaviour change also work through social networks. In this case study, the main node for social networks is burial groups. Burial groups are based on a close kinship social network and identity, which are important for the formation of mutual insurance networks (De Weerdt and Fafchamps, 2011) and their importance in facilitating transmission of behaviour change messaging has been well recorded. A series of studies on prevention of river blindness prevention in south-western Uganda (our exact areas of research) and Cameroon have recorded a couple of issues regarding social network effects. First, Ugandan villages where preventive health intervention for river blindness was implemented through burial groups, registered higher success rate for prevention (Katabarwa et al., 2000a) and treatment (Katabarwa et al., 2010a,b) than Cameroonian villages where burial groups either did not exist or were not used. Secondly, in villages with burial groups, researchers found higher levels of health education (Katabarwa et al., 2004) and the interventions were cost-effective due to dependence on community social capital (Katabarwa et al., 2015, 1999). These studies, therefore, concluded that using traditional systems such as burial societies was important for meeting preventive health and behaviour change targets (Katabarwa et al., 2000a). Possibly, the most important premise that comes from these studies is that burial groups facilitate information diffusion, learning, as well as adhering to norms and agreed codes of conduct which might translate into health improvements for the members.

Supplementary services: The second pathway is supplementary services from which CBHI participating households benefit from. Based on discussions with CBHI staff and hospital administration, it was found that CBHI participating households received both educational and non-educational services which gave them an edge over their non-CBHI participating households. One service is health promotion outreach services. Health promotion, information provision on CBHI, a complaints and feedback platform are some of the aims of outreach activities in communities. For instance, at the time of this survey, outreach teams carried out child nutrition assessments, information on infant feeding practices as well as referring the severely malnourished to the hospital. The research team was further told of a new community-based epilepsy and a mental health program that was under planning. In addition, it also came to our knowledge that the hospital also operated a energy-saving cooking stoves project where households in CBHI could buy cooking stoves at discounted prices. Figures on circulation of these cookstoves were not verified however, it was acknowledged that a majority had been purchased by households in CBHI. Furthermore, earlier in 2009, the CBHI scheme also provided water treatment filters which could be purchased at a discounted price by the households in insurance. These outreach services are conducted with CBHI burial groups only and not all other burial groups. Although it is not possible to ascertain perfect exclusion of households not in CBHI, this information suggested that CBHI households possessed elevated initial conditions to benefit from these supplementary services. This perception was supported by statements from survey participants. One participant noted:

"We have not had a field officer coming to teach us anything about insurance apart from one who came to teach us on how to treat drinking water and store it safely in a jerry can."

While another added;

"Some groups meet every month and save their money with the group treasurer, discuss sanitation issues in our families and the whole group. There is more that we talk about and discuss in the group than insurance only."

It is therefore plausible that these services and information acquired, act as both a pathway and as a supplement to CBHI so that the effect of CBHI membership is made more prominent. The centrality of community-based structures such as kin-related social systems is underlined.

4.5 Conclusions.

The effect of health insurance on preventive health has been studied less in health insurance research and more precisely the effect of CBHI which is on an increasing trend in developing countries. In this chapter, an effort is made to contribute to this gap in health insurance research by analysing the effect of CBHI on seven health outcomes. The literature review reveals two important issues. The first one is that interventions to improve the uptake of preventive health treatments are short-term and often have adoption and targeting bottlenecks and the desired behaviour change remains elusive. There is, therefore, a need for new strategies and interventions which are cost-effective and have long-term rather than momentary effects. Secondly, interventions in the literature are mainly household targeted intervention and interventions that utilise community targeting are far apart. This study brings these two aspects together - CBHI as a community targeted intervention for preventive health.

After employing IPW, robust evidence is found to the effects that CBHI has on several preventive health strategies. The study finds that enrolment in insurance was causally associated with improvements in four of the seven outcomes in the overall population. In particular, this was an increase in the probability of using LLIN by 28.5 percentage points, 20 percentage points increase in the probability of water treatment, 13 percentage points increase in the probability of receiving iron supplementation and a 23 percentage point increase in the probability of deworming under-5 children. There were positive but not significant effects regarding hand-washing and iron supplementation. For those who were in CBHI, we find larger coefficients and significance levels regarding the uptake of LLIN, vitamin A supplementation, iron supplementation deworming and even the uptake of PCV. The study results arrive at different conclusions than Yilma et al. (2012) whose findings in Ghana indicated a reduced use of LLIN. However, they supplement findings by Panda et al. (2015) in India, who found that households in CBHI were more likely to have better knowledge and practice of preventive health strategies.

This study is important for policy considerations in two aspects. The first one is on strategies to increase the uptake of preventive health. Developing countries face high disease burden from easily preventable illnesses such as malaria, and other waterborne and vectorborne diseases such as diarrhoea. Efforts to promote the use of preventive health strategies and remedies have significant bottlenecks regarding their long-run effectiveness and sustainability after interventions have ended. This research, therefore, gives credence to pathways with low economic costs and wider coverage. For instance, community social support networks have been found to be important in malaria prevention in sub-Saharan Africa (Apouey and Picone, 2014). Utilising the community involvement in insurance schemes can also generate wider network effects as we find in this study. The second policy consideration is in regards to the health insurance evolvement in Uganda to facilitate the legislation of a national health insurance scheme (Basaza et al., 2013). For the last two decades or so, there have been policy discussions at different levels, to introduce a national health insurance scheme that incorporates the different types of private insurance with a social health insurance scheme. However, as Basaza et al. (2013) narrates, these discussions have so not yet resulted in any policy. This research should provide the involved policymakers with more evidence about the impact of insurance, and in particular CBHI on preventive health.

This study also draws attention to the need for more research on health insurance effects on both preventive and curative health outcomes in sub-Saharan Africa where there exists a dearth of research in this area despite growth in CBHI in the region. The reasons for a dearth of research on health insurance and health outcomes, especially in developing countries can be partly attributed to the unavailability of data. For instance, in Uganda, the Living Standards Measurement Survey that has carried out four household surveys between 2009 and 2014 removed the health insurance module from the survey tool possibly due to the very low response rates. In this study, modest contributions are made to health research in Uganda, by carrying out the first survey on a CBHI programme. To the best of our knowledge, this becomes the first empirical study on the child health impacts of health insurance of any kind in Uganda. Such studies could have happened on a probably wider scale than done here, but targeted data does not exist as yet. Future research on CBHI in western Uganda on CBHI issues might consider building on this study to evaluate long-lasting outcomes and impacts of insurance in rural poor communities.

CHAPTER

FIVE

CONCLUSIONS, POLICY RECOMMENDATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This thesis tackles an important issue in health insurance research with a focus on developing countries and using a large community-based health insurance scheme in Uganda as a case study. The motivations for this work lie in the fact that very little is known on how health insurance enrolment (CBHI in particular) influences the health outcomes of the targeted populations. While promoting health insurance for financial protection at the household level and health systems financing at the macro level, are important, it is equally important that research does not lose focus of other effects especially, health improving effects. In refocusing research to these issues and asking some of the less asked questions in health insurance research, the focus is to know if membership in CBHI has effects on child health outcomes and if it has an effect on utilisation of both home-based and clinical preventive health strategies. From this case study, the thesis also gives the first quantitative assessment of the determinants of CBHI enrolment in Uganda.

5.0.1 Main findings

5.0.1.1 Determinants of CBHI enrolment

Basaza et al. (2013) give a timeline of the establishment of a national health insurance scheme in Uganda that goes as far back as 1995 and is not yet complete, in that the scheme is not yet implemented. Even with such a slow policy-making process, one of the missing components is a quantitative understanding of how the determinants of households can influence enrolment into such a programme. The proposed social insurance scheme will cover government public workers through an involuntary statutory enrolment. It is expected that the remaining population will enrol on a voluntary basis. And yet, no quantitative evidence exists on what would determine voluntary enrolment.

Using this case study of Kisiizi CBHI, it is established that the determinants of enrolment and staying in voluntary CBHI were in Uganda were in agreement with previous research. Household socioeconomic welfare played an important role in that the odds of enrolling and continued participation increased as household welfare improved. The amount of information and knowledge about CBHI assessed by knowledge of premiums, husband's employment status and the number of burial groups in the villages and social influence from village leaders and were found to be other important determinants of enrolment in CBHI. Results indicate child's age, parental secondary education, larger household size, burial group size interface with a TBA were the main variables associated with reducing the odds of enrolment.

The work of Jehu-Appiah et al. (2012) helps to investigate further on household perception on CBHI, an emerging focus issue in CBHI enrolment literature. Overall positive perceptions were found to be significantly associated with increasing the odds of CBHI enrolment by over 1.5 times. Particularly, we find that perceptions on management of the schemes were more important for enrolment while it was found that perceptions on premiums were associated with reducing the odds of enrolment by up to 38 percent. By and large, perceptions were not significantly associated with staying in CBHI. However, perceptions on premiums were associated with reducing odds of staying in CBHI for one more year by almost 9 percent. Both knowledge and perceptions about insurance are formed based on the quantity and quality of information people had. This implies that the frequency of information campaigns was important to facilitating forming of positive perception and building trust in scheme management and service providers. This finding is therefore in agreement with previous qualitative work carried out in Uganda that find that information gaps and low trust levels were responsible for low enrolment (Basaza et al., 2008).

The finding regarding the importance of socioeconomic welfare levels reveals two things. The first one is that even in arrangements of existing solidarity such as burial groups, exclusion based on socioeconomic capability can be present. In this case study, odds of enrolment were considerably skewed towards households in upper quintiles. It is important to note that the Uganda draft national insurance scheme bill proposes the scheme to cover the indigents. This would be expected to reduce exclusion from participation. However, progress on the policy formulation front is not yet conclusive on how indigents will be assessed and covered. Instead, it reveals contentions on how the policy might look like. Such contentions might actually derail an already very slow policy-making process. Given the fact that socioeconomic exclusion is established, it is important for the government and even such community-driven endeavours for health insurance, to have the poorest at the centre of coverage since the poorest households would be the ones with even higher disease burden. For instance, one way in which the government's future scheme will be able to include the poorest is through progressive premiums, including exemptions in some cases as has been recently implemented in Rwanda (Kalisa et al., 2015). Another way is to develop community-based health insurance schemes within the broader framework of social protection programming that has gained scale in developing countries. Emerging evidence from Ethiopia indicates that poor householdsŠ utilisation of health services and income protection are better improved when households benefit concurrently from social protection programmes and CBHI (Shigute et al., 2017a,b).

In addition, it is important that governments and other private not for profit organisations that engage in providing health insurance to informal and rural people put into consideration perceptions of their target population. Organisation could invest in providing adequate information through both community informal gatherings as well as utilising media. Adequate and appropriate information is useful in constructing positive perceptions that further facilitate enrolling and staying enrolled in CBHI.

5.0.1.2 Effect of CBHI on child stunting

This research further finds that membership in CBHI was causally associated with improving child health outcomes. More specifically, the study aimed at measuring the effect on stunting, a condition which is a result of long-term and intergenerational poor nutrition and which has wide-ranging detrimental effects on health and human capital development. A 2SRI method, an estimation method useful for health services studies with non-linear relationships (Terza et al., 2008) was implemented. This helped to combine two aspects of CBHI as a treatment, the treatment status and length of time in years a household had participated in CBHI. Findings indicated that each year a household participated in CBHI was associated with a 5.7 percentage point reduction in the probability of stunting. Given that these results were linear in coefficients, this result translates into 28.5 percentage point reduction in the probability of stunting during the child's under-5 lifespan. These results are in agreement with previous studies in Rwanda and the Philippines which indicated that similar insurance programmes had positive effects on stunting reduction (Lu et al., 2016) and wasting reduction (Quimbo et al., 2011) respectively. Data further indicate that households in CBHI were more likely to spend less on health care and utilise other health services more than their non-CBHI counterparts. This could point to the possibility of financial protection and savings.

5.0.1.3 Effects of CBHI on the utilisation of preventive health services and strategies

Finally, Chapter 4 of this thesis investigates the effect of CBHI membership on the utilisation of preventive health services. Preventive health remains at the forefront when discussing public health and health economics research because a very disproportionate disease burden in developing countries is borne by easily preventable illnesses such as malaria and other water, vector and airborne illnesses. The chapter borrows its relevance from bottlenecks in several interventions that have been applied to increase the utilisation of preventive services. For instance, interventions using cash transfers have inclusion and exclusion errors and have often been questioned for their sustainability in aid-dependent developing countries. Interventions that use price subsidies have been found to have price inelasticity and yet providing services for free has often resulted in wastages and misuse. These bottlenecks make it relevant for this study to focus on the possibility of preventive health being nudged and improved through CBHI participation, an intervention which households already appreciate and participate in. An IPW estimation strategy that follows on earlier work of Hirano and Imbens (2001) is implemented. This strategy helps to precisely estimate the causal effects of CBHI participation on a range of preventive health strategies by controlling for the observable determinants of CBHI participation and creating a control group of households for whom the propensity score weight of taking CBHI would be similar to that of CBHI participants. In particular, the effects on using LLINs for all household members, water treatment, owning a handwashing facility on a household latrine, vitamin A supplementation, iron supplementation, child deworming and receiving a new vaccine for child pneumonia, PCV are estimated. Significant ATEs associated with using LLIN, water treatment, receiving iron supplement and deworming were established. Though in only 3 of the outcomes, the differences between the potential outcomes and the ATEs were significant, the large differences reveal the actual depth of the effects and hence the policy relevancy. For the CBHI participating households, significant effects were found regarding LLIN, handwashing, iron supplementation, deworming and PCV. It is postulated that the length of time households participate in CBHI matters on behaviour change and utilisation of preventive services. However, by and large, the households with more intensive participation did not have higher utilisation levels. The results were largely driven by households with less intensive CBHI participation assessed as 1-4 years of CBHI membership which points to the need for consistent health promotion and refining strategies for controlling possible moral hazard.

The results regarding LLIN utilisation diverge from a previous study in Ghana (Yilma et al., 2012), an issue we speculatively attribute to the differences in insurance schemes assessed regarding the centrality of community-wide social networks. In this case study, community-wide social networks are expressed through membership in burial groups as a vehicle for accessing insurance. From a series of papers on the prevention of river blindness in south-western Uganda, the importance of burial groups is underscored both for the organisation of communities and as nodes of information diffusion. There is no major role played by such groups in the Ghana research by Yilma et al. (2012). In this case study, these burial groups play an important role too in facilitating social learning and behaviour change.

But while these results give special attention to burial groups and how they might facilitate social learning, this is also a caveat that is underlined. In other words, these results might not hold or be interpreted beyond the scope of such groups. Indeed complementary to works by Katabarwa and colleagues, research by Marcel Fafchamps, Stephan Dercon and colleagues in Ethiopia and Tanzania has also shown that such groups are essential in creating insurance networks. However, burial groups are not that widespread across Uganda. In some parts of the country, they are only recently evolving (Jones, 2009; Ntozi and Nakayiwa, 1999). These results should, therefore, be read with this in mind. As a matter of fact, CBHI can exist outside burial groups' framework of programming. Indeed, in many other countries, CBHI has been based on individual household enrolment. On this basis, it is recommended that for Uganda, more research would have to be carried out in order to fully understand these determinants and effects. It is noted that the most recent Uganda National Household Survey has already taken this direction by asking some questions about willingness to join voluntary insurance, for which they find that over 40 percent of Ugandans were willing to join a voluntary health insurance programme (UBOS, 2017).

One other limitation of this study is the estimation strategy in Chapter 4. Like all other propensity scores based analysis method, inverse probability weighting controls for all possible observables that can determine treatment assignment. This implies that it is not possible to account for the unobservables. While there is no doubt about the efficacy of the model selection used for CBHI participation, more robust casual effects can be estimated with richer data (for instance panel data) that can apply more improved methods of causal inference.

APPENDIX

A

APPENDICES

A.1 Supplementary Tables to Chapter Three

Table A.1: First Stage and Reduced form Regressions

	(CBHI Status)		(Stunting prevalence)	
	Coff	se	Coff	se
Cluster CBHI demand	0.801	(0.620)	0.628	(0.459)
Leader & social influence	0.159**	(0.068)	−0.009	(0.043)
Burial group size	−0.018***	(0.004)	0.001	(0.003)
Child's age (months)	−0.015	(0.027)	0.090***	(0.020)
Child's age square	0.000	(0.000)	−0.001***	(0.000)
Mother's age (24.9 years)	0.000	(.)	0.000	(.)
25 - 34.9 years	0.204	(0.211)	−0.121	(0.165)
35 - above	0.160	(0.275)	0.057	(0.212)
Child is male	0.147	(0.168)	0.075	(0.127)
Birthweight	−0.175	(0.170)	−0.171	(0.124)
Health facility delivery	0.213	(0.186)	0.048	(0.140)
LLIN per capita	0.156	(0.301)	0.085	(0.239)
Exclusive breastfeeding	0.207	(0.186)	0.346**	(0.134)
Catholic	0.249	(0.191)	−0.224	(0.150)
Parental (some) sec educ	−0.365*	(0.211)	−0.226	(0.161)
Wealth index (quintile 1)	0.000	(.)	0.000	(.)
Quintile 2	0.032	(0.252)	−0.520**	(0.203)
Quintile 3	0.374	(0.303)	−0.460**	(0.205)
Quintile 4	0.340	(0.271)	−0.575***	(0.214)
Quintile 5	0.805**	(0.340)	−0.518**	(0.247)
Food adequacy	0.050	(0.193)	0.209	(0.143)
Household diet diversity score	0.038	(0.079)	−0.038	(0.056)
Husband employment -casual labour	0.296	(0.197)	0.041	(0.149)
Wife employment -casual labour	−0.556*	(0.323)	−0.002	(0.215)
Household size 4	−0.062	(0.204)	−0.419**	(0.165)
Proportion of under five	0.781	(0.861)	0.631	(0.647)
Access to information	−0.072	(0.082)	−0.057	(0.063)
Neighbour in CBHI	0.135	(0.241)	0.009	(0.168)
Waiting time	0.000	(0.001)	0.001	(0.001)
No of group memberships	0.825***	(0.132)	0.021	(0.079)
Interface with TBA	−0.163	(0.190)	−0.185	(0.157)
No of burial groups in village	0.157***	(0.048)	0.051	(0.036)
Distance to hospital	−0.210***	(0.061)	−0.029	(0.047)
No of household in village	−0.001	(0.004)	−0.000	(0.003)
Village has a health centre	−0.302	(0.365)	−0.245	(0.284)
Village has a school	0.187	(0.267)	0.100	(0.220)
Village economy-pastoralism	1.088**	(0.503)	−0.149	(0.301)
Village economy-banana cultivation	0.304	(0.337)	−0.078	(0.233)
Constant	−0.046	(1.319)	−0.575	(0.886)
Pseudo R-squared	0.5532		0.1251	
N	464		464	

Bootstrapped standard errors in parentheses Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Predictive mean probability of stunting at different years of insurance

Years in CBHI	Prob Stunting	Delta-Method Std.Error	z	P>z	95% Conf. Interval
0	0.531	0.044	11.980	0.000	0.444 - 0.617
1	0.488	0.110	4.440	0.000	0.273 - 0.704
2	0.484	0.121	4.010	0.000	0.247 - 0.720
3	0.344	0.082	4.200	0.000	0.184 - 0.505
4	0.416	0.120	3.460	0.001	0.181 - 0.652
5	0.353	0.091	3.890	0.000	0.175 - 0.531
6	0.147	0.060	2.470	0.014	0.030 - 0.264
7	0.319	0.125	2.540	0.011	0.073 - 0.565
8	0.164	0.115	1.430	0.154	-0.061 - 0.389
9	0.123	0.089	1.380	0.167	-0.051 - 0.296
10	0.133	0.082	1.610	0.108	-0.029 - 0.294
11	0.083	0.059	1.420	0.157	-0.032 - 0.199

Table A.3: Robustness checks: Zero Inflated Poisson and Zero Inflated Negative Binomial model results.

	(Main Model 2SRI)		(First stage ZIP)		(First stage ZINB)	
	AP	se	AP	se	AP	se
Years in CBHI	−0.057***	(0.022)	−0.049**	(0.021)	−0.049***	(0.019)
Child's age (months)	0.032***	(0.007)	0.032***	(0.007)	0.032***	(0.006)
Child's age square	−0.000***	(0.000)	−0.000***	(0.000)	−0.000***	(0.000)
Mother's age (base <24.9)						
25-34.9 years	0.027	(0.067)	0.021	(0.067)	0.021	(0.058)
$35 years$	0.110	(0.086)	0.096	(0.085)	0.096	(0.076)
Child is male	0.028	(0.048)	0.027	(0.048)	0.027	(0.042)
Birthweight	−0.068	(0.046)	−0.068	(0.046)	−0.068*	(0.041)
Facility delivery	0.014	(0.053)	0.013	(0.053)	0.013	(0.047)
LLIN per capita	0.031	(0.100)	0.039	(0.103)	0.040	(0.082)
Exclusive breastfeeding	0.136***	(0.050)	0.128**	(0.050)	0.128***	(0.044)
Catholic	−0.054	(0.052)	−0.054	(0.052)	−0.054	(0.048)
Parent secondary (some) educ	−0.077	(0.061)	−0.080	(0.061)	−0.080	(0.053)
Wealth Index (base: Quintile 1)						
Quintile 2	−0.193**	(0.079)	−0.186**	(0.079)	−0.186***	(0.068)
Quintile 3	−0.140*	(0.081)	−0.146*	(0.081)	−0.146**	(0.070)
Quintile 4	−0.191**	(0.084)	−0.196**	(0.083)	−0.196***	(0.072)
Quintile 5	−0.152	(0.098)	−0.159	(0.098)	−0.158*	(0.084)
Food adequacy	0.072	(0.056)	0.066	(0.057)	0.066	(0.048)
HDDS	−0.015	(0.022)	−0.015	(0.022)	−0.015	(0.019)
Husband employment -casual labour	0.019	(0.059)	0.013	(0.059)	0.013	(0.051)
Mother's employment -casual labour	0.009	(0.084)	0.008	(0.084)	0.009	(0.072)
Household size 4	−0.119*	(0.062)	−0.126**	(0.062)	−0.126**	(0.055)
Proportion of under five	0.093	(0.250)	0.117	(0.249)	0.116	(0.216)
Access to information	−0.020	(0.024)	−0.017	(0.024)	−0.017	(0.021)
Neighbour in CBHI	0.036	(0.066)	0.032	(0.066)	0.032	(0.056)
Waiting time	−0.000	(0.000)	−0.000	(0.000)	−0.000	(0.000)
No of groups' membership	0.050	(0.035)	0.050	(0.035)	0.050	(0.031)
Interface with TBA	−0.043	(0.057)	−0.040	(0.057)	−0.040	(0.049)
No of burial groups in village	0.029**	(0.014)	0.026*	(0.014)	0.026**	(0.012)
Distance to hospital	−0.031*	(0.018)	−0.029	(0.018)	−0.029*	(0.016)
No of household in village	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)
Village has a health centre	−0.118	(0.110)	−0.112	(0.111)	−0.112	(0.096)
Village has a school	0.050	(0.087)	0.050	(0.087)	0.050	(0.074)
Village economy-pastoralism	0.010	(0.115)	−0.004	(0.114)	−0.003	(0.103)
Village economy-banana cultivation	0.038	(0.074)	0.033	(0.074)	0.033	(0.064)
Residuals	0.077***	(0.024)	0.069***	(0.023)	0.069***	(0.020)
N	464		464		464	

Bootstrapped standard errors in parentheses Significance levels $*p < 0.1, **p < 0.05, ***p < 0.01$

A.2 Supplementary Tables to Chapter Four

Table A.4: Covariate balancing by weighted regressions

Variables	Insur	Std Err	Constant	Std. Err	Obs	R-squared
Child's age	−3.251	2.336	32.69***	1.89	464	0.012
Mother's age	0.282	1.453	29.23***	1.331	464	0
Birthweight	−0.216*	0.128	3.334***	0.116	464	0.034
Parental secondary education	0.286	0.46	−1.117***	0.303	464	
Health facility delivery	−0.219	0.421	0.558*	0.337	464	
Catholic	−0.006	0.458	0.262	0.362	464	
Wealth index	0.079	0.177	0.00864	0.091	464	0.001
Neighbour in CBHI	0.034	0.524	1.032***	0.286	464	
Husband employment - casual	−0.353	0.498	−0.281	0.445	464	
Wife employment - casual	−0.294	0.467	−2.458***	0.28	464	
Household diet diversity score	0.183	0.201	4.160***	0.149	464	0.006
Household size	0.164	0.333	5.725***	0.236	464	0.002
Log burial group size	0.043	0.14	3.987***	0.136	464	0.002
Log number of burial groups in village	0.139	0.159	1.573***	0.11	464	0.009
Satisfaction with health workers	0.366	0.467	1.772***	0.364	464	
Perception index	0.112	0.095	−0.149*	0.086	464	0.012
Social & Leader influence	0.267	0.374	0.133	0.352	464	0.007
Access to information	0.34	0.308	0.114	0.184	464	0.015
Interface with TBA	0.375	0.431	−0.356	0.347	464	
Know premiums	0.439	0.515	0.409	0.336	464	
Waiting time	−18.11	34.39	116.3***	32.75	464	0.006
Village has a TBA	0.094	0.407	1.259***	0.339	464	
Village has a health centre	0.054	0.45	−0.764**	0.326	464	
Village has a school	−0.192	0.43	0.669*	0.359	464	
Village economic activity- banana	−0.067	0.127	0.374***	0.116	464	0.005
Village economic activity- pastoralism	−0.645	0.705	−1.668***	0.262	464	
Distance to nearest health centre	2.286**	1.058	3.426***	0.318	464	

Robust standard errors

Significance levels $***p < 0.01, **p < 0.05, *p < 0.1$

Table A.5: Covariate balancing after treatment effects weighting

	Standardized differences		Variance ratio	
	Raw	Wghted	Raw	Weighted
Child's age	−0.094	−0.230	0.943	1.000
Mother's age	0.023	0.041	1.033	0.853
Child is male	−0.288	−0.396	0.834	0.675
Log Birthweight	−0.027	0.194	0.999	1.089
Parental secondary education	−0.264	0.127	0.788	1.140
Health facility delivery	0.116	−0.106	0.975	1.052
Catholic	0.576	−0.003	0.950	1.003
Wealth index	−0.004	0.068	0.525	0.968
Wealth index squared	−0.216	−0.010	0.279	0.437
Neighbour in CBHI	0.958	0.015	0.324	0.986
Husband employment - casual	0.233	−0.172	1.151	0.926
Wife employment - casual	−0.287	−0.074	0.431	0.778
Household diet diversity score	0.149	0.152	1.051	1.137
Household size	0.021	0.082	0.795	0.878
Log burial group size	−0.781	0.092	1.521	0.617
Log number of burial groups in village	1.345	0.195	0.528	0.921
Satisfaction with health workers	0.205	0.120	0.655	0.761
Perception index	0.010	0.228	1.146	0.919
Satisfaction*Perception index	0.072	0.236	1.198	0.954
Social & Leader influence	0.398	0.181	0.704	0.580
Access to information	0.460	0.253	1.150	1.359
Interface with TBA	−0.452	0.187	1.028	1.034
Interface with TBA*access to information	0.355	0.396	0.733	1.711
Know premiums	1.760	0.209	0.507	0.877
Waiting time	0.358	0.157	1.729	0.882
Village has a TBA	0.027	0.038	0.970	0.950
Village has a health centre	−0.278	0.025	0.884	1.021
Village has a school	−0.193	−0.092	1.110	1.057
Village economic activity- banana	0.061	−0.142	1.069	0.910
Village economic activity- pastoralism	−0.762	−0.209	0.177	0.615
Distance to nearest health centre	−0.404	0.010	0.221	0.787

Robust standard errors

Significance levels *** p<0.01, ** p<0.05, * p<0.1

Table A.6: ATEs from Weighted Least Squares regressions

	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A supplement	(5) Iron supplement	(6) Deworming	(7) PCV
CBHI participation	0.285***	0.200*	0.062	0.160	0.131**	0.234**	0.032
	(0.092)	(0.106)	(0.056)	(0.123)	(0.064)	(0.117)	(0.066)
PO (No CBHI)	0.274***	0.444***	0.066**	0.627***	0.060***	0.591***	0.217***
	(0.064)	(0.093)	(0.018)	(0.116)	(0.019)	(0.112)	(0.050)
R Squared	0.0377	0.0111	0.0283	0.0414	0.0596	0.0222	0.0014
N	464	464	464	464	464	464	464

Robust standard errors in parentheses
Significance levels *** p<0.01, ** p<0.05, * p<0.1

Table A.7: ATEs from Nichols (2008) re-weighting scheme

	(1) LLIN	(2) Water Treatment	(3) Hand washing	(4) Vitamin A supplement	(5) Iron supplement	(6) Deworming	(7) PCV
CBHI participation	0.285***	0.200*	0.062	0.160	0.131**	0.234**	0.032
	(0.092)	(0.106)	(0.056)	(0.123)	(0.064)	(0.117)	(0.066)
PO (No CBHI)	0.274***	0.444***	0.066**	0.627***	0.060***	0.591***	0.217***
	(0.064)	(0.093)	(0.018)	(0.116)	(0.019)	(0.112)	(0.050)
R Squared	0.0767	0.0349	0.2709	0.0259	0.0409	0.0542	0.0013
N	464	464	464	464	464	464	464

Robust standard errors in parentheses
Significance levels *** p<0.01, ** p<0.05, * p<0.1

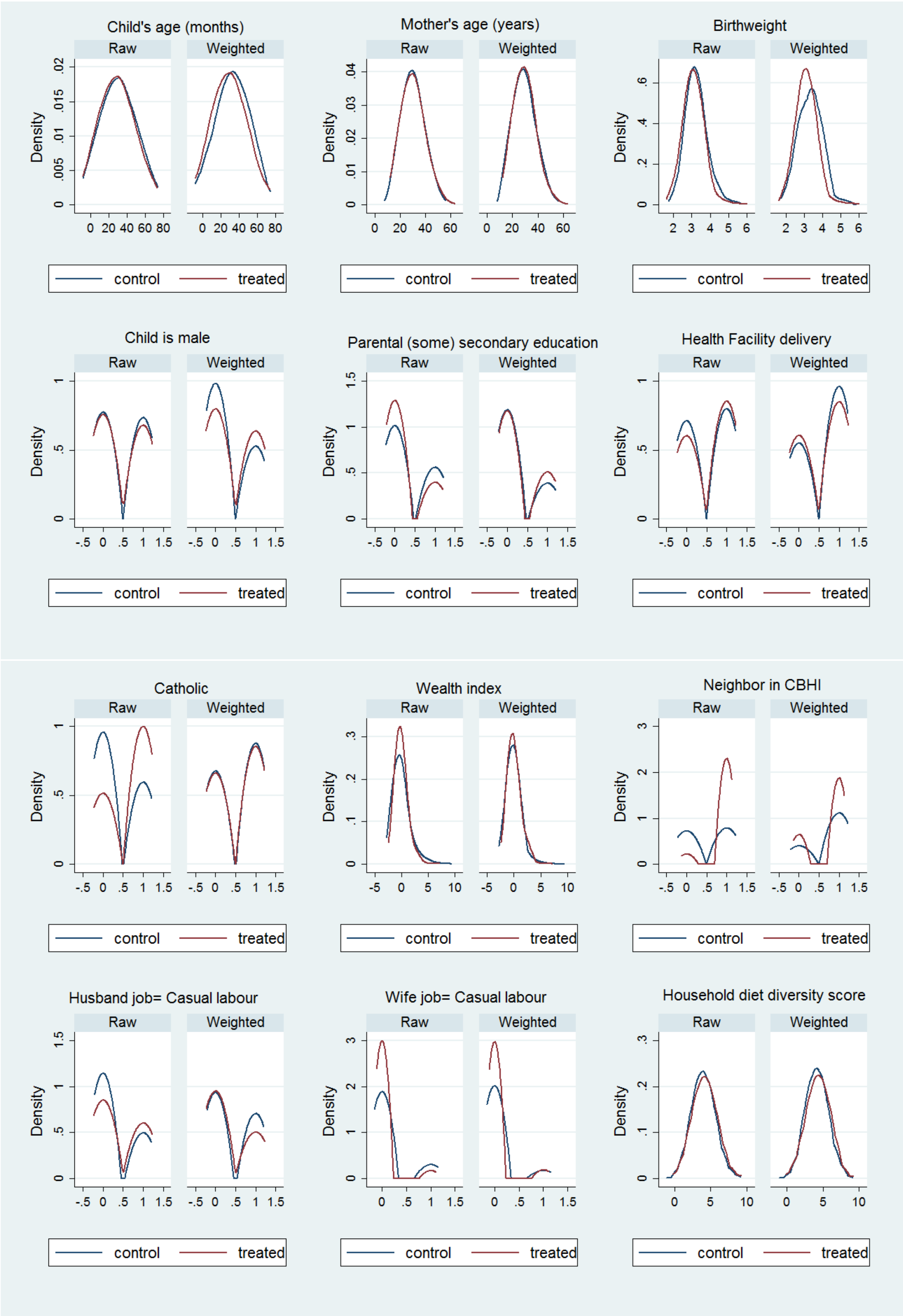
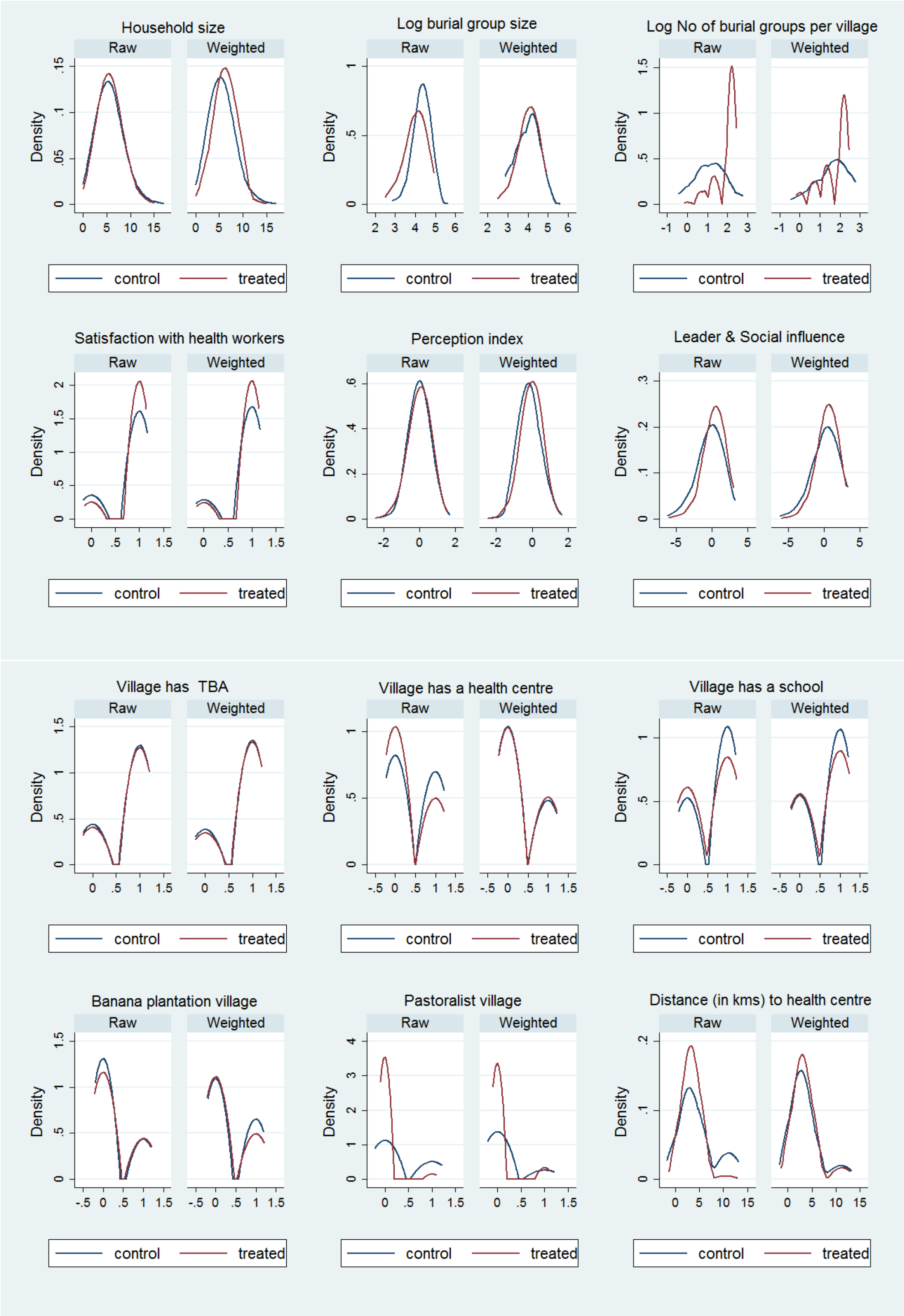
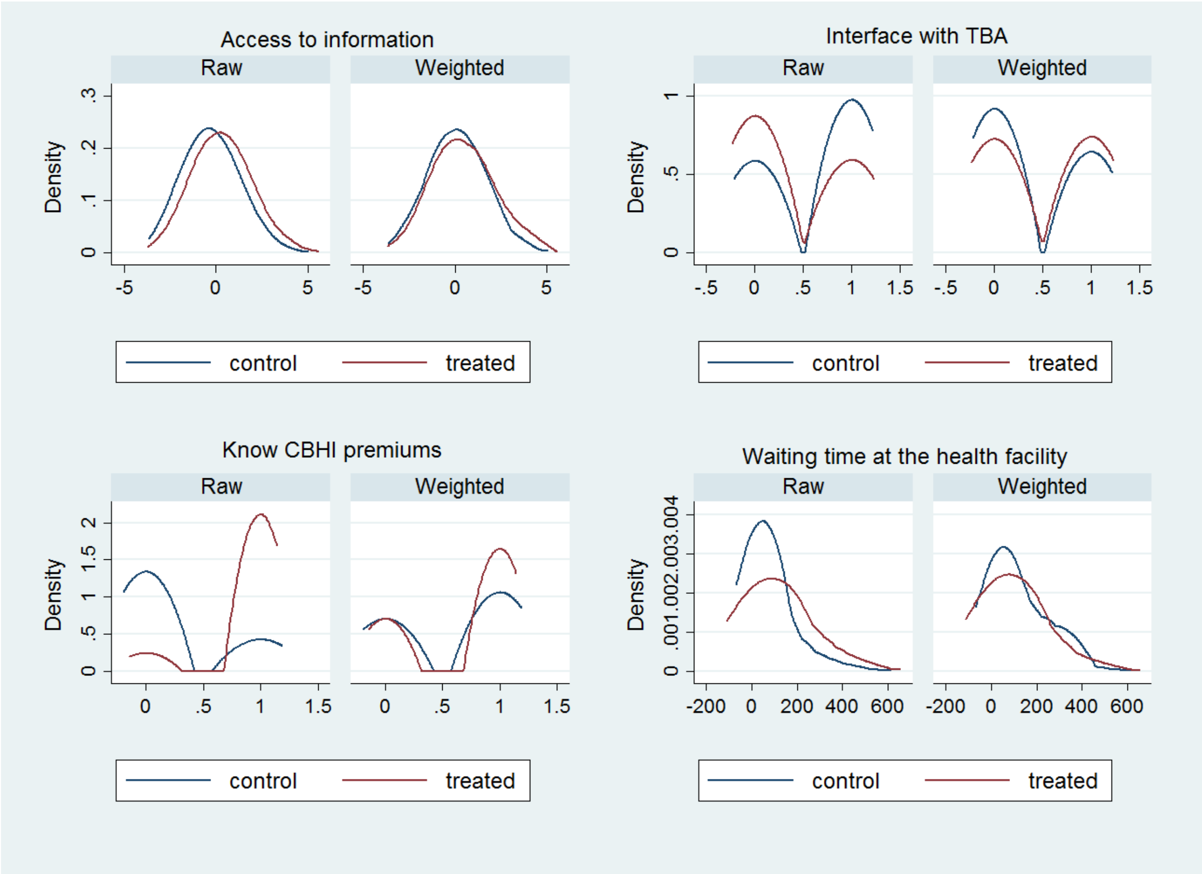


Figure A.1: Balance plots between treatment and control observations across covariates


Household size
Log burial group size
Log No of burial groups per village
Satisfaction with health workers
Perception index
Leader & Social influence
Village has TBA
Village has a health centre
Village has a school
Banana plantation village
Pastoralist village
Distance (in kms) to health centre
Raw
Weighted
Density
control
treated



Access to information
Raw
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Raw
Weighted
Density
0
.5
1
1.5
2
0
.5
1
1.5
control
treated
Waiting time at the health facility
Raw
Weighted
Density
0
.001
.002
.003
.004
-200
0
200
400
600
control
treated

A.3 Procedure for the imputation for birthweight

Normally, for conventional multiple imputation procedures, an assumption is made that data is missing completely at random or simply missing at random (MAR). However, as Angrist and Pischke (2015, p. 21) notes, it is rarely the case that data is MAR and the presumption that responders are systematically different from non-responders is plausible. It is therefore suspected that the missing data is missing not at random (MNAR). To be certain of this, t-tests are conducted to study the mean differences on a set of selected observables. From the table below showing t-test results, it can observed that in the data that there are significant differences between the households which birthweight was observed and the ones which it was not observed across several variables.

Table A.8: Systematic differences between observed birthweight and missing birthweight by across selected observables

	Observed birthweight		Missing birthweight			
	mean	Std err	mean	Std err	mean diff	t-stat
SES	0.220	0.092	−0.273	0.078	−0.493***	−3.97
Distance to facility	11.179	0.217	11.770	0.399	0.591	1.37
Perception about health insurance	0.116	0.107	−0.144	0.123	−0.261	−1.61
Satisfaction with health services	0.065	0.179	−0.081	0.217	−0.146	−0.52
HDDS	4.245	0.082	3.874	0.083	−0.371**	−3.13
Parental education	0.374	0.030	0.217	0.029	−0.156***	−3.68
Household size	5.062	0.120	5.763	0.156	0.701***	3.61
ANC services	0.463	0.031	0.338	0.033	−0.125**	−2.74
All child immunizations	0.261	0.027	0.329	0.033	0.0678	1.60
Iron supplementation	0.125	0.021	0.073	0.018	−0.0517	−1.83
Child deworming	0.739	0.027	0.744	0.030	0.00466	0.11
Vitamin A Supplementation	0.813	0.024	0.720	0.031	−0.0934*	−2.39
Treated water	0.565	0.031	0.478	0.035	−0.0864	−1.85
Protected water source	0.708	0.028	0.609	0.034	−0.0995*	−2.26
Handwashing facilities	0.156	0.023	0.053	0.016	−0.103***	−3.55
Stunted	0.385	0.030	0.469	0.035	0.0834	1.81
Diarrhoea	0.265	0.028	0.237	0.030	−0.0279	−0.69
Fever	0.128	0.021	0.111	0.022	−0.0173	−0.57
Cough (ARI)	0.514	0.031	0.493	0.035	−0.0209	−0.45
Waiting time	92.553	7.084	83.739	7.142	−8.813	−0.87
Insured neighbour	0.681	0.029	0.705	0.032	0.0244	0.56
Observations	257		207		464	

t-statistics in parentheses $*p0.05, **p0.01, ***p0.001$

These differences appear in about eight of the twenty selected observables. Normally, if only a handful of variables present statistically significant differences in the means of the observables, it can be assumed that the differences are due to random chance (Rubin, 1987, p. 202) and hence MAR. However, in this case, more than one third of the observed variables have significant differences as shown in the table above. the MAR non-ignorability assumption (Royston, 2009) can therefore not be confidently assumed.

The imputation

STATA Multiple Imputation (StataCorp, 2013) procedure was used for imputation. The procedure generally assumes that data is MAR (Royston, 2009) so additional assumptions to incorporate for non-random missingness (Horton and Kleinman, 2007) are required. (Rubin, 1987) suggested some MNAR imputation procedures which include incorporating fixed transformations that increase or decrease the values of MAR depending on the assumptions used, or incorporating in the imputation procedure a distortion in the probability of drawing values to use in the imputation function. This distortion produces random rather than systematic draws. A predictive linear regression model is specified containing all variables in the data that can improve the R-squared (Kenward and Carpenter, 2007). For imputation of missing data of MNAR nature, there is need to add a term that incorporates a term that accounts for the missingness. For instance, (Rubin, 1987, p. 204) suggests that a constant term of 20 percent can be added on or subtracted from the imputed values to account for the assumption that the missing values are 20 percent lower or higher than the observed. Or that a constant value can be added or subtracted from half of the imputed values as a distortion on the fixed transformation or introduce a distortion in the probability of drawing values to impute using the function of the value to be imputed (Enders, 2010). However, Rubin's suggestions are thought to be arbitrary and instead of adding a model specific standardized mean difference is advised (Marchenko and Eddings, 2011). In this case, after executing the linear regression, the missing values are replaced with the predicted values plus a random noise equivalent to a random number with mean of 0 and standard deviation being the standard error of the linear prediction. This implies that each imputed observation is replaced with to a random number that accounts for the non-random missingness. A seed of 12345 is set for reproducibility.

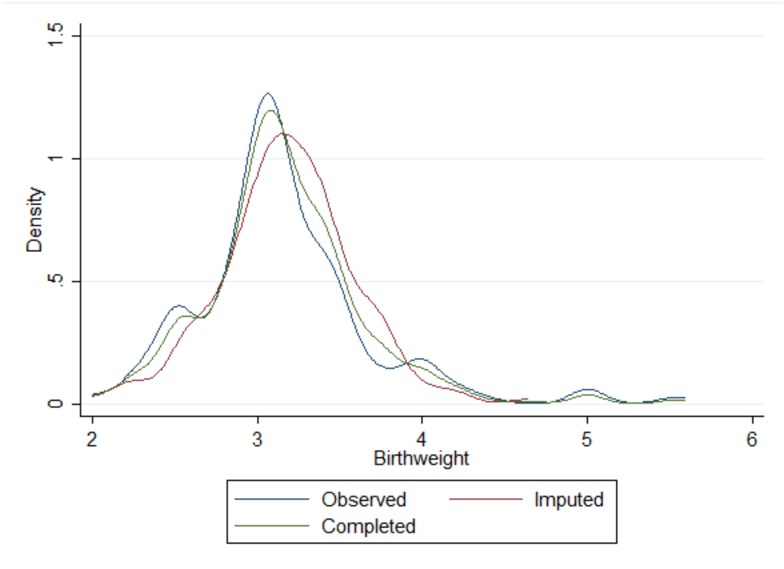
In the table below, results of the imputation are shown. The overall mean of birthweight increases by 1.3 percent from 3.15 to 3.19 kilograms. The proportion of low birthweight also increases slightly from 6.2 percent to 6.5 percent.

Table A.9: Examination of the imputation exercises for birthweight

	obs	mean	min	max	sd
Imputed birthweight	207	3.23	1.59	4.86	0.540
Observed birthweight	257	3.15	2	5.6	0.532
Complete birthweight	464	3.19	1.59	5.6	0.517
Low birth weight					
Imputed low birth weight	207	0.0676	0	1	0.225
Observed low birth weight	257	0.0622	0	1	0.242
Complete low birth weight	464	0.0647	0	1	0.234

The k-density graph below shows the distribution of the observed values, imputed valued and completed values of birth weight. The graph shows that the distribution of completed values fit smoothly along the distribution of observed values. This is the desired scenario.

Figure A.2: K-density distribution of MNAR multiple imputation procedure



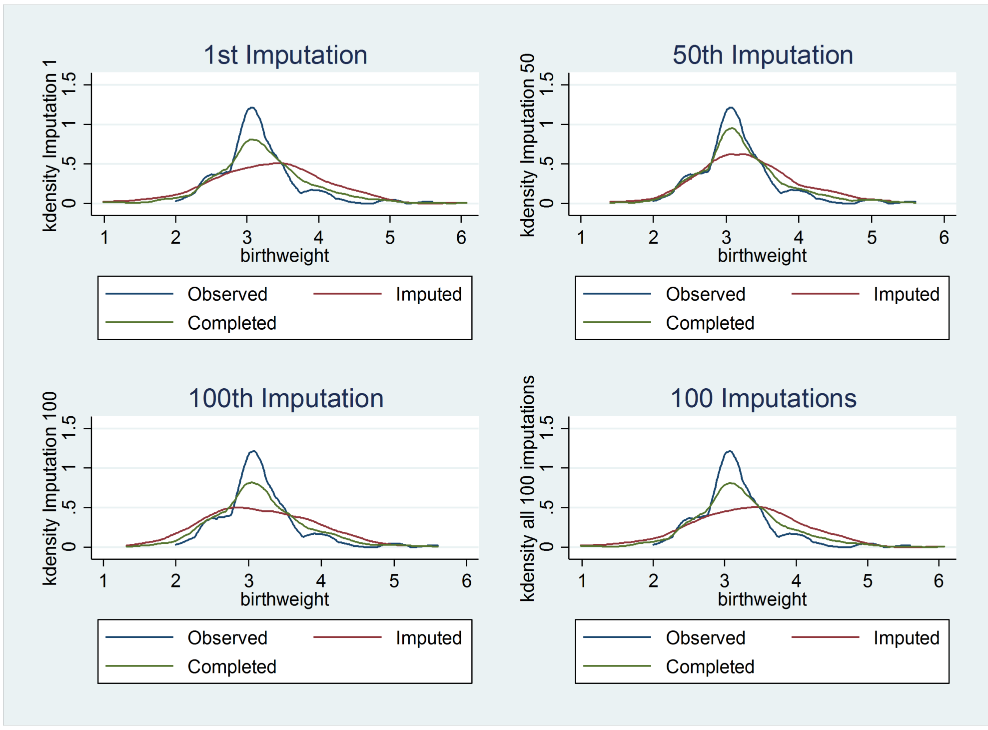
If the data were MAR or missing completely at random, the imputed distribution would be expected to be close to or fully fitting into the observed distribution curve (Kenward and Carpenter, 2007).

Sensitivity checks for imputation

Normally, when imputation procedures assume that data is MAR, one method of sensitivity analysis is to assume that the data is MNAR and compare results in relation to how close the imputations get close to what is observed (Eddings and Marchenko, 2012). If the data are MAR, it would be expected that the assumption of MNAR would yield results not so different from each other. In this case, it is very clear that the data is MNAR and so comparing with the results if it had been assumed that the data was MAR in one robustness and sensitivity check. The expectation is that the results would be different and the MNAR - complete values would be close to the observed values than the MAR results, to make the MNAR justifiable. The MAR is therefore executed. To improve the performance of MAR results, it is recommended to increase the number of imputations (Rubin, 1987; Van Buuren et al., 1999). With a large proportion of missing values, between 50 and 200 imputations can be sufficient (Horton and Lipsitz, 2001; Kenward and Carpenter, 2007). Following this recommendation of increasing the number of imputations, sensitivity analysis was carried out with 100 imputations under a MAR assumption and compare the 1st, 50th and the 100th imputation and a combination of all 100 imputations.

The comparison of the generated values of missing birthweight - based on the kernel density graphs above show that even after 100 imputations, the distribution of completed observations still performs worse than in the study's assumption of MNAR. The assumption of MAR was found to still be inadequate to deliver imputations

Figure A.3: Performance of MAR sensitivity check



close enough to the observed values when compared to with MNAR. The assumption on MNAR is therefore sufficient for the imputation procedure chosen. This method of sensitivity test has been applied elsewhere in health services research (Longford et al., 2000).

Table A.10: OLS Model predicting birthweight.

Variable	Coefficient	Std error
Child Stunted	−0.0204	(0.083)
Mother's age	0.003	(0.007)
No of years in insurance	−0.012	(0.016)
Child is male	−0.027	(0.083)
Age of child	−0.003	(0.003)
Vitamin A supplement	−0.193∗	(0.113)
All immunisation	0.017	(0.096)
U-5 LLIN usage	−0.040	(0.112)
Exclusive breastfeeding	0.162∗	(0.088)
Religion: base = catholic		
Protestant	0.135	(0.107)
Other	0.140	(0.145)
Parental education	−0.110	(0.093)
Household = 4	−0.012	(0.128)
Used fertilizer	0.035	(0.164)
Used pesticide	−0.114	(0.105)
Had a good harvest	−0.011	(0.089)
In a farmer's group	0.063	(0.130)
Extension services	−0.074	(0.104)
Farmer training	0.011	(0.126)
Improved bathroom	0.146	(0.287)
Improved toilet	0.214	(0.192)
Handwashing facility	0.215∗	(0.123)
Perceptions on insurance:		
Premiums	−0.096∗∗	(0.042)
Health beliefs	0.033	(0.042)
Social influence	−0.061∗∗	(0.025)
Scheme management	−0.010	(0.040)
Quality of care	−0.028	(0.036)
Financial protection	0.016	(0.022)
Scheme convenience	0.046	(0.036)
HDDS	−0.002	(0.034)
Has an insured neighbour	−0.082	(0.101)
Casual employment	0.062	(0.162)
Land size	−0.012	(0.037)
Livestock	0.014	(0.022)
Listen to radio daily	0.094	(0.093)
No of group membership	−0.022	(0.052)
Differential distance	−0.162	(0.128)
Household altitude	−0.001	(0.001)
Village has a:		
Health centre	−0.078	(0.214)

Continued on next page

Table A.10 – continued from previous page

Variable	Coefficient	Std error
Road	0.314	(0.250)
School	0.112	(0.292)
No of insurance groups in village	0.095	(0.069)
Village economy: base = pastoral villages		
Banana villages	0.434	(0.296)
Forest villages	0.683*	(0.395)
Trade villages	0.026	(0.215)
Attended at least 4 ANC	0.059	(0.106)
Household size	0.010	(0.038)
At least 3 meals a day	0.021	(0.082)
Housing endowments	−0.017	(0.033)
Household assets	−0.028	(0.031)
Rooms-people ratio	0.231	(0.175)
Married	0.187*	(0.107)
Satisfaction with:		
Time with health workers	0.054	(0.073)
Waiting time	0.062	(0.040)
Health workers' explanations	−0.039	(0.086)
Not rushed by doctors	−0.042	(0.098)
Information from doctors	0.009	(0.121)
Advice on your illness	−0.029	(0.119)
Information on tests done	0.000	(0.083)
Conduct of health workers	0.015	(0.112)
Doctor's explanations	−0.025	(0.104)
Care showed by health workers	0.103	(0.113)
Interest by health workers	0.033	(0.115)
Treated with dignity	0.026	(0.098)
Conduct of other hospital staff	−0.037	(0.101)
Help from other staff	−0.114	(0.103)
Kindness & courteousness from other staff	0.078	(0.119)
Perception of fair costs	−0.026	(0.042)
High toilet coverage	0.471*	(0.264)
Protected water source	−0.191	(0.177)
Connected to leaders	−0.036	(0.096)
Lent in six months	0.048	(0.088)
Borrowed in six months	0.080	(0.092)
Iron supplement	−0.149	(0.130)
Deworming	0.194**	(0.098)
Waiting time	0.000	(0.000)
Constant	3.234*	(1.643)
R-squared	0.279	
Observations	257	

Standard errors in parentheses ***p < 0.001, **p < 0.01, *p < 0.05

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