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Impact of Community-Based Health Insurance on Child Health Outcomes: Evidence on Stunting from Rural Uganda

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Abstract

While community-based health insurance (CBHI) becomes increasingly integrated into health systems in developing countries, there is still limited research and evidence on its probable health impacts beyond its functions for health financing or for facilitating access to services. Using a cross-sectional data from rural south-west Uganda, we apply a two-stage residual inclusion instrumental variables method to study the impact of community health insurance on stunting in children under five years. Results indicate that each year a household was enrolled in insurance was causally associated with a reduction in the probability of stunting of 5.7 percentage points. Predictive marginal effects show that children in households which have had insurance for at least 5 years had a probability of stunting of only 0.353 compared to 0.531 for children in households with no insurance. Households in CBHI were more likely to attend more free antenatal and post-natal care visits and report fewer illnesses and reported less health expenditures. Moreover, CBHI enrolment was also associated with reduced health costs. We recommend that developing countries should facilitate the expansion of community health insurance scheme not only for their contribution to health financing but even more for mortality and morbidity aversion.

Keywords: Community-based health insurance, Child Stunting, Two-Stage Residual Inclusion, Rural Uganda

JEL Codes: I130, I150, I100, I555

1 Introduction

Community-Based Health Insurance (hereafter CBHI) schemes are a particular form of health insurance systems emanating from community social support systems (Criel, Atim, Basaza, Blaise, & Waelkens, 2004), often working in the rural informal sector, and operating without profit motivations (Bennett, Creese, & Monasch, 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, Waelkens, & Criel, 2005; Ekman, 2004). Over the last few decades, CBHI has evolved as an essential buffer for financial protection and enabling access to health services, especially in poor rural communities. They currently form essential building blocks to achieving universal health coverage in developing countries (Wang & Pielemeier, 2012) and have been adopted across many countries with varying forms and levels of government involvement.

Over the last couple of years, there has been an increasing number in studies on CBHI, with significant focus on enrolment and drop out (Atinga, Abiiro, & Kuganab-Lem, 2015; De Allegri et al., 2006; Dror et al., 2016; Panda, Chakraborty, Dror, & Bedi, 2014), facilitating access to health services (Jutting, 2004; Mebratie, Sparrow, Alemu, & Bedi, 2013; Smith & Sulzbach, 2008; Sood & Wagner, 2016), financial protection (C. V. Nguyen, 2012; H. T. H. Nguyen, Rajkotia, & Wang, 2011; Sepehri, 2014; Sepehri, Sarma, & Oguzoglu, 2011), and wider welfare as well as economy-wide impacts on risk-coping and managing shocks (Asfaw & von Braun, 2004a, 2004b; Landmann & Frölich, 2015; Yilma et al., 2014, 2015). However, evidence remains thin on the impacts of CBHI on the health indicators of the insured, especially children. For instance, of the several systematic reviews in recent years (Adebayo et al., 2015; Dror et al., 2016; Ekman, 2004; Mebratie et al., 2013; Reshmi, Sreekumaran, & Unnikrishnan, 2016; Spaan et al., 2012)), only one, (Acharya et al., 2013) reported some impacts on health outcomes, in six of the nineteen papers they review. Acharya et al. (2013) found this surprising, that research had paid limited attention to understanding if health insurance had any effects on health outcomes of the insured in developing countries. This study, therefore, seeks to respond to this research gap.

On the other hand, stunting remains a major problem to the health of children in developing countries. Low height for age affects an estimated 165 - 170 million children in the world and affects developing countries disproportionately (Prendergast & 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 & Paxson, 2010; Dewey & Begum, 2011; Glewwe, Jacoby, & King, 2001; Vogl, 2014). Thought stunting has reduced in the last couple of years, an estimated 29 percent of under-5 children were stunted in 2016 (UBOS & ICF International, 2012). Extrapolating from the 2014 census (17.7% of 34.8 million under 5 years), indicated that about 1.8 million children were stunted in 2014. Nutritionists have warned 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).

The main aim of this paper is to therefore combine these two issues, on the one hand and opportunity of the growth of insurance platforms in developing countries, in Uganda in particular and on the other a long-standing child health challenge. This paper uses cross-sectional data from south-western Uganda, collected in an area with a large CBHI scheme and studies the effect of CBHI participation on child stunting. One of the challenges of studying the effect of health insurance on health outcomes is the endogeneity between health insurance and health outcomes (Levy & Meltzer, 2008). To account for such endogeneity the paper applies a novel Instrumental Variable (IV) approach, the Two-Stage Residual Inclusion (2SRI) approach (Terza, Basu, & Rathouz, 2008; Wooldridge, 2015). Using the framework outlined by Terza (2017), the method facilitates not only the analysis of the decision to enrol in CBHI but also incorporates CBHI intensity, measured by the number of years a household participated in CBHI.

This paper's major contribution to the health economics literature is the demonstration that CBHI can influence health dimensions 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 more evidence that health of children improves when their households enrol in CBHI is provided.

The rest of this paper is organised as follows. Section 2 positions this paper on why stunting an avoidable child health problem in Uganda. Section 3 reviews the current literature on the effects of CBHI and other voluntary health insurance programs on health outcomes. Section 4 gives the empirical strategy of the paper by elaborating on the data and instrumental variable identification strategy. Section 5 provides the detailed results and section 6 gives a discussion and concludes the paper.

2 Health insurance and health outcomes in developing countries

Our work adds to a just emerging body of research in response to this research gap on health insurance and health outcomes. Evidence is still thin and largely mixed. A couple of papers find positive effects. For instance, in Nigeria, (Hendriks et al., 2016, 2014) studied the impact of health insurance on hypertension over the short and medium term. In the first paper, (Hendriks et al., 2014), they find that systolic blood pressure reduced by 5.2 mm Hg more in villages with CBHI while diastolic blood pressure reduced twice as much compared to villages with no CBHI. After 5 years of the CBHI intervention, Hendriks et al. (2016) find sustained effects indicating that systolic blood pressure maintained a greater reduction of 4.97 mm Hg in CBHI villages. Sood and Wagner (2016) found that insurance had positive effects on post-operation recovery self-assessed measurements. Wang, Yip, Zhang, and Hsiao (2009) found overall improvements on the health status of the insured in rural China, while Pan, Lei, and Liu (2016) also report improved self-reported health for those enrolled in the urban insurance program in China.

However, a couple of other papers find no evidence of any effect. While studying the effect of health insurance expansion on child mortality in Costa Rica, Dow and Schmeer (2003) find very limited evidence on this causal effect. In a similar manner, Thornton et al. (2010) do not find significant effects in Nicaragua. Likewise, in China, Lei and Lin (2009) do not find any improvement in self-reported health status of the insured, while Sood et al. (2014) do not find any improvement in mortality of the insured in India. Probably a more extreme finding is Fink, Robyn, Sié, and Sauerborn (2013) who find that health insurance in Burkina Faso was associated with increased mortality of the older enrolees, a result they attribute to the declining quality of care.

A couple of studies that look into child health outcomes also provide mixed results. Fink et al. (2013) did not find any effects on child health measured by mortality. However, three studies find positive effects on child anthropometrics. Lu et al. (2016) used demographic and health surveys data, and health facilities data, and found that enrolment in Rwandan CBHI was associated with reducing the probability of stunting for children between 6 and 24 months by 14 percentage points. Quimbo, Peabody, Shimkhada, Florentino, and Solon (2011) found that voluntary insurance had a causal effect of up to 12 percentage points reduction in wasting in the Philippines while Schoeps et al. (2015) found that the risk of mortality was 46% lower for children in insurance compared to their uninsured counterparts in Burkina Faso.

There are a couple of differences between this paper and these studies on child health and new dimensions that this paper contributes to the literature. 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, Nzayirambaho, & Kakoma, 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) have access to rich demographic and health survey data, they chose a narrow 6-24 months population. We enhance on this by widening the age group to all under-fives and not a section of them. The Philippines study (Quimbo et al., 2011) uses is of limited application to many sub-Saharan African countries because of the lack of clinical data. While clinical data might be more precise in the measurement of health outcomes, in countries like Uganda it would miss a large sub-population with limited access to health facilities. For instance, only 58 percent of mothers delivered in health facilities in Uganda (UBOS & ICF International, 2012). This survey was therefore designed with this in mind and hence captures all households at both ends of health facility access and utilisation.

3 The empirical strategy

3.1 The Data

Between August 2015 and April 2016, we carried out a household survey in south-western Uganda in two districts in which the Kisiizi hospital CBHI scheme operates. The Kisiizi CBHI scheme is one of the 21 and the biggest CBHI scheme in Uganda, providing insurance coverage to close to 42,000 individuals. The scheme is a provider-based scheme, run by a rural hospital. At the time of this study, households paid premiums ranging from Uganda shillings 10,000 (equivalent to approximately US$3) per person for households of up to 11 people to Uganda shillings 28,000 (approximately US$8) for households of 2 people.[1]

Membership in insurance is based on group such that for a household to be insured, it has to be part of group. Most of the groups are pre-existing informal funeral insurance groups, which are integral in the promotion of different kinds of insurance(De Weerdt, Dercon, Bold, & Pankhurst, 2007; Dercon, De Weerdt, Bold, & Pankhurst, 2006; Dercon, Vargas, Clarke, Outes-Leon, & Taffesse, 2014). For a funeral insurance group to enrol its members, two conditions have to be met. The first is that the group has to have at least 30 households. For these smaller groups, all the households have to subscribe. The second condition pertains to larger groups. In these larger groups, some with more than 100 households, at least 50% of households have to subscribe and all members of the subscribing households are required to enrol. However, while enrolment is group based, the scheme is not a typical group insurance. There is no joint liability within the groups and households enrol at an individual basis with individual premiums. Households enrol as a full unit, such that, in principle, when a household enrols, all members of the household are enroled and once some members are drop out, the whole household drops out. Another important feature of this scheme is the timing of coverage. In order to further control moral hazard and adverse selection, members are fully covered once they have been in insurance for more than one year. Once a household member is ill with in only one year of enrolling, insurance covers only 10% of the cost. These kinds of strategies to limit adverse selection have been applied in other community insurance scheme. For instance in a Nigerian scheme, enrolled people wait for about 36 days before they can be covered by insurance (Bonfrer, Van De Poel, Gustafsson-Wright, & van Doorslaer, 2015). In the case of this scheme, a waiting time of one year is certainly more conservative. Typically, insurance covers basic primary care, maternity

[1] Average annual exchange rate of US$ 1=3400 UGX in 2015. According to the 2012 National Household Survey (UBOS, 2014) average annual household incomes for Kigezi region were Uganda shillings 4.1 million, derived from reported monthly income of Uganda shillings 343,000. This implied 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

care, surgeries, and outpatient and inpatient services. Outpatient services for chronic illnesses and substance abuse related illnesses and injuries are excluded.

In partnership with this scheme, we used a multi-stage simple random sampling, and surveyed 464 households in fourteen (14) villages in two (2) districts. The survey modules included a household demographic module which collected information on household occupancy; a child and maternal health module which collected information on health care seeking behaviour for mothers and children; a nutrition module which collected information on household food availability and intake. The survey collected detailed information on household social and economic welfare using durable assets holdings and other endowments in agriculture, water and sanitation, and housing. The health insurance and social connectivity modules collected information regarding household insurance status, group membership and participation, and knowledge of insurance such as premiums and benefit 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 probably better understanding of health insurance, we also collect birth registry data recorded in birth registers in health facilities with a functioning maternity facilities. Within our region of data collection, data is collected from six health facilities. We present this data as part of summary statistics and use only household data in the casual estimations.

Ethical approvals for data collection was conducted by the Mengo Hospital Research and Ethics Review Committee and an ethical certificated was provided by the Uganda National Council of Science and Technology (Reference Number SS-39369). Further ethical reviews were undertaken by the Centre for Development Research, University of Bonn research committee and the local research partner, Kisiizi Hospital Research Committee. Verbal consent was obtained from the district administration health teams, local government authorities, village leaders and respondents.

3.2 Identification strategy: Two-Stage Residual Inclusion Instrumental Variable method

A lot of literature attests to the fact that insurance increases health care utilisation because it removes financial barriers to access. However, in some instances, utilisation of care might lead to over consumption of care which might in turn result in spending of health, hence defeating the financial protection purpose (Wagstaff & Lindelow, 2008). But irrespective of the financial protection situation after insurance, we take that consumption of more 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 & Meltzer, 2004, 2008). Our identification strategy will therefore utilise an instrumental variable approach to overcome endogeneity problems (Angrist & Imbens, 1995; Angrist, Imbens, & Rubin, 1996). Instead of the conventional Two-Stage Least Squares (TSLS) instrumental variable approach, we employed a Two-Stage Residual Inclusion (2SRI). The 2SRI method, also called the Control Function method introduces extra regressors which break the correlation between the endogenous explanatory variable and the unobservables affecting the outcome (Wooldridge, 2010, p. 126). A couple of reasons are provides as to why the 2SRI method is more appropriate for a study like ours (Cai, Small, & Have, 2011; Terza et al., 2008; Wooldridge, 2010). First, it provides a straight forward way of testing the hypothesis that the endogenous explanatory variable is actually endogenous buy looking at the behaviour of the residuals. Secondly, the model is robust in addressing endogeneity in health economics studies of non-linear relationship that the conventional two-stage least squares and two-stage predictor substitution methods.

Moreover, our treatment variable measured two related parts; namely the treatment and the treatment intensity, we used an alternative estimation of the 2SRI which combines these two parts, following Terza (2017) Stata code implementation guidelines. It is a common occurrence that when treatment is offered, treatment intensity varies across the treated (Angrist & Imbens, 1995) but also the proportion of non-compliers is large and non-ignorable (Mullahy, 1998). In a case like this, Mullahy (1998) proposes a two-part model that assumes that the probability of the treatment, $Pr(y>0|x)$ is governed by a probability model like a Probit in the first part and that $E[ln(y)|y>0,x]$ and is a linear function of x, e.g., $E[ln(y)|y > 0, x] = x\beta$ (part two).

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. Using Mullahy's smoking and birthweight data (see (Mullahy, 1997, 1998)), Terza (2017) employs this version of a non-linear instrumental variable model to analyse of the effect of maternal smoking on birthweight. One other convenience of a 2SRI model is the ease with which the tests of endogeneity and endogeneity control are done. 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 & Stock, 1997; Stock, Wright, & Yogo, 2002; Stock & Yogo, 2005). In addition, when the included residuals are significant, it shows that endogeneity was indeed present and also well controlled for in the model (Gibson et al., 2010; Pizer, 2009; Staub, 2009).

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, required 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 (2017). 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.

$$\text{CBHI Status}_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \epsilon_i \tag{1}$$

Where CBHI Status$_i$ is the treatment dummy corresponding with 1 if household i participated in CBHI and 0 otherwise,, Z$_i$ is a vector of the instruments used, X$_i$ 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.

$$\text{CBHI Years}_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \epsilon_i \tag{2}$$

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. The residuals η_i, are derived as the differences between the observed insurance intensity and the product of predicted insurance status and predicted mean intensity.

$$\eta_i = \text{CBHI Years}_i - \alpha_1 * \alpha_2 \tag{3}$$

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.

$$\text{Stunted}_i = \beta_0 + \beta_1 \text{CBHI Years}_i + \beta_2 X_i + \beta_3 \eta_i + \epsilon_i^{2SRI} \tag{4}$$

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 (Terza, 2017; Wooldridge, 2010). We bootstrap up to 1,000 replications for all the estimated models.

3.3 The instrumental variables

The standard validity of our instruments is hinged on meeting two basic conditions, that; (1) the instruments have a strong predictive association with the treatment (CBHI status) and, (2) that they do not have any significant association with our outcome (stunting prevalence), such that the only effect of the instruments on the outcome is through the treatment. In this regard, we adopt three instruments, 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. Apart from the challenges of finding one very strong instrument, using three instruments also helps in model efficiency gains (Chao & Swanson, 2005; Hansen, Hausman, & Newey, 2008; Roodman, 2009). We expound on each of them.

Latent Village CBHI demand rate: a common IV in health economics studies is aggregated prevalence of a treatment at community or sub-national level. For instance, Stukel et al. (2007) used regional catheterisation rates as an instrument for a patient's probability of receiving a cardiac catheterisation treatment while Jung and Streeter (2015) used the fraction of individual 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.

The intuition in which village latent CBHI demand rate is constructed is slightly different. All the none-CBHI households were asked a hypothetical question to state their preference in joining a village group they did not already belong to, to capture their latent preference to join CBHI. While moving from one burial group to another is very restrictive, it is possible when leaders agree to the move and only when the groups belong to the same kin association. Expressing a wish to join a burial group that participated in CBHI showed a household's latent demand. Village CBHI latent demand rate was therefore constructed as the ratio of uninsured households who wish to join a CBHI-participating burial group in a village.

$$\text{Village CBHI demand rate} = \frac{\text{Non CBHI households wishing to join a CBHI burial group}}{\text{Total non CBHI households}} \tag{5}$$

The 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) and in this data, all respondents belonged to one. In societies with egalitarian and mutual assistance traits in regards to risk sharing and mutual insurance, group sizes matter (De Weerdt & 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 increase free riding (Stahl & Haruvy, 2006). But also, the larger the group the higher the per capita utility from risk sharing (Genicot & Ray, 2003) and therefore the reduced need for taking on other formal insurance[2]. There are a number of ways in which the group size is expected to influence enrolment decisions. As we mention earlier, requirements set by the scheme that pertain to groups affect which groups can have their members enrolled and those who may not. Whilst preference might be given to larger groups because more members can monitor each other for adherence (Carpenter, 2007), smaller groups have more cohesion (Stahl & Haruvy, 2006) and therefore easy to manage. We, therefore, expect a negative association between group size and enrolment status.

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. Since household enrolment was group facilitated, it was expected that group leaders, often clan elders, have a significant role they play in influencing households to enrol. Social influence was there assessed as a composite perception indicator, following previous studies that show that perceptions regarding social influence were important for household enrolment in insurance (Jehu-Appiah, Aryeetey, Agyepong, Spaan, & Baltussen, 2012). Respondents were asked five statements with Likert Scale responses

[2]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.

ranging from 1 to 5; where 1 corresponded with "do not agree" and 5 corresponded with "completely agree".[3] Using Principal Components Analysis, 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.

The validity of these instruments is hinged on how they meet the relevance condition and the exclusion restriction. Table 1 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 1.

Table 1: 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

[3]The five questions are (1) We learn from out neighbours about the things we do such as which community groups to join (2) Village opinion leaders influence us about the programmes we enrol in, such as insurance (3) Our friends and other extended family members influence our decision to enrol in insurance (4) Enroling 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 affects our decision to enrol in insurance

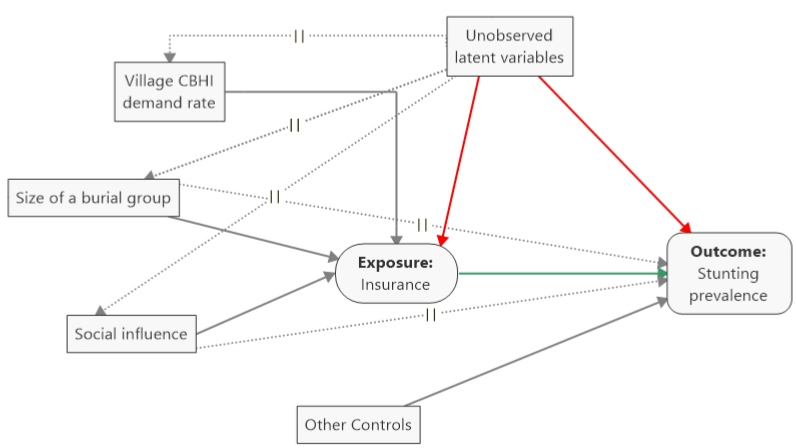
variations of the instrumental variable methods (estimating the Sagan or Hansen tests) but for our multi-step approach, we use a regression based approach that follows Wooldridge (2010, p 136-137). We estimate the equation:

$$\eta_i = \beta_1 Z_{ij} + \beta_2 X_{ij} + \epsilon \tag{6}$$

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 overidentification test statistic which is N (our sample) times the R-squared, given as nR^2. Our over-identification test statistic is 3.898 with an associated p-value of 1.000 and we can comfortably say that our instrumental variable model does not reject the over-identification restrictions.

This causal relationship can be illustrated using Direct Acyclic Graphs (DAGs) (Stanghellini, 2004; Textor, van der Zander, Gilthorpe, Liśkiewicz, & Ellison, 2017), which illustrates that the IVs are perfect predictors of CBHI status, hence the causal link from the exposure to the outcome. It also further illustrates that there is no relationship between the IVs and stunting.

Figure 1: DAG for causal association of CBHI membership and stunting



4 Results

4.1 Descriptive results

Stunting is assessed using the World Health Organisation growth monitoring standards as a height-for-age Z-score with a standard deviation of -2 or less (Duggan, 2010). Overall, 42.2 percent of the children in the sample were stunted. Children in the lowest wealth quintile had a higher prevalence, of 58.5 percent while only 30.2 percent of children in the highest wealth quintile were stunted.

Figure 2: CBHI status

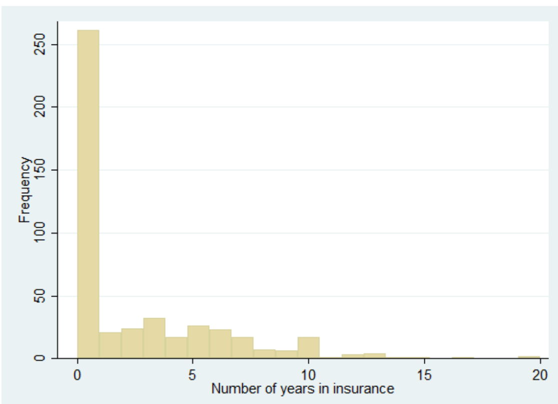
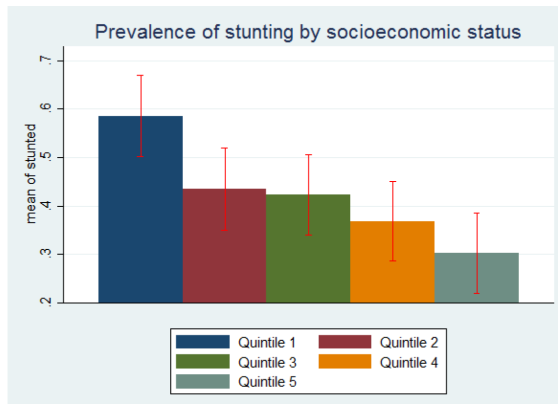


Figure 3: Stunting Prevalence



Our outcome of interest is stunting prevalence. Overall, 42.2 percent of the children in our sample had a height-for-age z-score less than -2 standard deviations, implying that they 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 assessed by the 2011 Demographic and Health Survey (UBOS & ICF International, 2012). In terms of the distribution of stunting, children in the lowest socioeconomic welfare index had a higher prevalence of stunting, just below 60 percent while only 30 percent of children in the highest wealth quintile were stunted.

43.8 percent of the households surveyed were enrolled in CBHI at the time of the survey. This was found to be substantially higher than previously reported insurance coverage of 15 percent in the same area (Dekker & Wilms, 2010) or 30 percent assumed by (Twikirize & O'Brien, 2012) indicating significant improvements in coverage. 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% 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% of the mothers had exclusively breastfed their youngest child for up to 6 months. Households had on average 0.4 LLIN 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 & ICF International, 2012), it was lower than the 2016 south-western average of 70.3 percent (UBOS & ICF, 2018). Some 63.4% of the mothers had exclusively breastfed their youngest child for up to 6 months. Only 16.8% of the households had all under-five children sleeping under a long-lasting mosquito net (LLIN). Furthermore, about 55.4% of the children had been born in a health facility. This was significantly higher than the regional average of 40.3% of children born in health facilities as measured in the 2011 DHS (UBOS & ICF International, 2012). In terms of distribution of respondents by village economies, some 18.1% of our respondents were located in forestry villages while 26.1% were in banana cultivation villages. Around 36.6% of the respondents were located in trading villages while the remaining 19.2% were from villages whose pastoralism was the main economic activity. More descriptive statistics are presented in the table below.

4.2 Empirical results

4.2.1 Main model results

The emprical results are presented in Table 3 below. In order to make the appropriate comparisons, results for probit regressions. After ascertaining that the models are well

Table 2: Descriptive results

VARIABLES	Mean	Min	Max	SD
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

fit[4], results indicate that there was no statistically significant association between CBHI participation and stunting. The main focus is therefore drawn on the average partial effects of the 2SRI- IV results presented in Model 3. After implementing the second stage probit regression of the probability of stunting, it is established that after controlling for 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.

Household socioeconomic welfare assessed by wealth quintiles was also very important in determining 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, 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. The probability of stunting for households living further from health facilities was lower by 3 percentage points.

Looking at the variables that increased the probability of stunting, it was found that an increase in the age of the child by one month was associated with increasing the probability of child stunting increased by 3.2 percentage points. However, the negative sign on the quadratic term indicated that probability of stunting increases in a declining trend and is not significant after about 32-33 months. 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

[4] 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, Lemeshow, & Sturdivant, 2013) show that the model is correctly specified.

Table 3: Impact of CBHI on stunting: Average Partial Effects

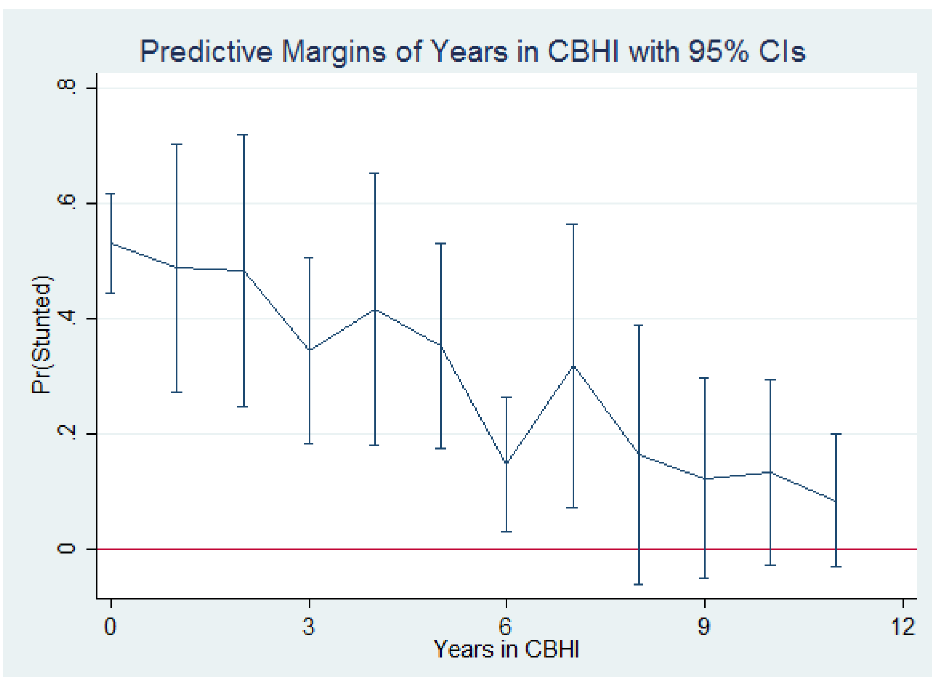
	(1)		(2)		(3)	
	Model 1: Probit		Model 2: Probit		Model 3: IV-2SRI	
	APE	SE	APE	SE	APE	SE
CBHI participation	0.038	(0.064)				
Years in CBHI			0.006	(0.009)	−0.057***	(0.022)
Child's age (months)	0.031***	(0.006)	0.031***	(0.006)	0.032***	(0.007)
Child's age square	−0.000***	(0.000)	−0.000***	(0.000)	−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 v0.014	(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.and Bootstrapped standard errors (1000 replications) for Model 3
*** p<0.01, ** p<0.05, * p<0.1

village indicates the depth of traditional informal social support strategies which in turn limits households' propensity for formal insurance.

To further elucidate on the effect on an extra year of CBHI participation, we plot predictive marginal probabilities for each year in CBHI. Results plotted in Figure 4 below indicate that the probability of stunting reduced consistently as households spend more years in CBHI. Specifically, it reduced from 51.5 percent for children in households with no CBHI participation to 37.6 percent in households with 5 years of consistent participation and remained statistically significant until seven years in CBHI. However, after five years, body mass index rather than stunting becomes the appropriate nutritional indicator. In addition, other households and individual child determinants influence the overall health status of a child. Nonetheless, the reduction in stunting, causally associated with CBHI participation is very clear.

Figure 4: Predictive margins of probability of stunting



One unexpected finding in these results is the size and sign of the coefficients of exclusive breastfeeding. As established, exclusive breastfeeding for at least six months of a child's life, is essential for child health through growth and nutrition (Kamudoni, Maleta, Shi, & Holmboe-Ottesen, 2015; Kuchenbecker et al., 2015) and therefore should reduce stunting too. We therefore expect a negative sign on the coefficient on this variable. However, we get a positive and statistically significant coefficient. We suspect that there might be measurement error through social desirability bias (Martinelli & Parker, 2009; Meshnick, 2015) or recall error, (Aarts et al., 2000; Bland, Rollins, Solarsh, Van den Broeck, & Coovadia, 2003; Gillespie, D'Arcy, Schwartz, Bobo, & Foxman, 2006) especially when a mother has had more children (Cupul-Uicab, Gladen, Hernández-Ávila, & Longnecker, 2009), as is the case in most developing countries like Uganda. The worst case scenario is that it influences the result that we get. We therefore omit the variable from the model and the results remain stable.

4.2.2 Some heterogeneous treatment effects

Boys and girls:

To understand how the effect of CBHI is distributed across boy and girls, we undertake separate outcome regressions. Whilst both boys and girls have negative coefficients, 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.

Moreover, the coefficient of stunting reduction among girls was not statistically significant and the coefficient of the residuals is not significant, indicating that endogeneity was controlled. Summary results showed that there was no significant difference between stunting prevalence for boys (43.0 percent) and girls (41.9 percent) therefore it is clear that the causal effect is skewed more to boys 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.

Table 4: Effect of CBHI membership on stunting between boys and girls

	Model 1: Boys		Model 2: Girls	
	Coeff	SE	Coeff	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)	

Bootstrapped standard errors (1000 replications)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Local Average Treatment Effects

Imbens and Angrist (1994) suggested a precise measure of treatment effects, the local average treatment effect, which under mild assumptions, estimates the treatment effect on only the subjects who receive the treatment. To estimate this, the outcome regression is undertaken on only the subsample of CBHI participant households. For these households, one extra year of CBHI participation was associated with reducing the probability of stunting by 14.8 percentage points, almost three times the effect on the whole population.

Table 5: Local average treatment effects

	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)	

Bootstrapped Standard errors (1000 replications)
***p<0.01, **p<0.05, *p<0.1

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 & Trivedi, 2009, Chap 17). To compare with our main model, (which following Terza (2017) 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, Pavlicova, & Nunes, 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 6: Robustness checks with alternative specifications

	(1) Main Model		(2) First stage ZIP model		(3) First stage ZINB 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 (1000 replications) in parentheses.
***p<0.01, **p<0.05, *p<0.1

5 Discussion and conclusion

The main results indicate that each year a household participated in insurance was associated wit reducing the probability of child stunting by 5.7 percentage points. Our data does not give us an opportunity to conclusively elucidate how this effect happens. However, we postulate three main pathways through which this effect might happen. The first is through social learning and social network effects associated with funeral groups through which households access insurance. Broadly, traditional funeral groups in south-western Uganda are meant for the primary purpose of funeral insurance but also perform other functions such as providing lending and borrowing services to their members at different extents. In extension to these services, funeral groups also provide a platform for infusing health information and facilitate behaviour change. Previous research on this front has primarily been focused on controlling of river blindness in the region and the authors find that not only was it cheaper to deliver health information to communities (Katabarwa, Mutabazi, & Richards, 1999) but also communities in which these platforms were used showed high rate of information take-up and more prevention than those in which such groups were used (Katabarwa, Habomugisha, Agunyo, et al., 2010; Katabarwa, Habomugisha, Eyamba, Agunyo, & Mentou, 2010; Katabarwa et al., 2015). However, at this stage we do not differentiate the funeral groups. The only difference is that some groups choose to participate in insurance and others do not. Indeed there could be some self-selection issues which out data cannot disentangle. However, what we observe is that funeral groups that participated in insurance had greater cohesion, evidenced by the number of times the met in month (2.4 times) compared to those that were not in insurance (2.1 times), a difference of 14 percent. This can also be appraised in the same way as intensive exposure to health information. Such has been found to have a significant effect on health behaviours such as adoption of long-lasting mosquito nets (Kilian et al., 2016; MacIntyre et al., 2012). In a related dimension, there might be social learning happening within the groups. These funeral groups are built on a strong cohesion of kin associations where behaviours and norms are established and in some instances, diversion from norms attracts reprimand (Katabarwa, 1999). We believe that in these highly socially controlled groups, positive learning happens when healthier households teach unhealthy households for instance on nutrition and hygiene. Our postulation here is supported by research in India that shows that households learn from each other on the adoption of improved sanitation and hygiene strategies (Shakya, Christakis, & Fowler, 2014, 2015).

Another channels through which these effects might come about is through service utilisation. Many studies have found that health insurance coverage greatly facilitates utilisation of health services for mothers (**?**) and for children (Gajate-Garrido & Ahiadeke, 2015; Singh et al., 2015). 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 in uninsured households. These differences give a compelling correlation through which health services utilisation can translate into health improvements.

Table 7: 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	04.96	03.45	06.13	0.0268	1.32
N	464	203	261	464	

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

Finally, out data is strongly suggestive of financial protection, which would facilitate savings and consumption. It has been found elsewhere that health insurance is associated with an increase in households' consumption of both food and non-food goods (Bai & Wu, 2014; Wagstaff & Pradhan, 2005). These findings would be in line with a large body of literature that shows that health insurance provided considerable financial protection. To test this in our data, we ran OLS regressions on the association between CBHI participation and household income and also between CBHI participation and reported health expenditure. The results indicated a significant negative association between CBHI participation and health expenditure, implying a possibility of financial protection. In this way, households would be able to release extra resources for food and non-food consumption that could have a positive effect on child health.

Table 8: Association of household income and CBHI participation and CBHI participation and cost of care

VARIABLES	(1) CBHI Participation	(2) Cost of Participation (ugx)
Household income (log)	-0.0145	
	(0.0697)	
CBHI participation		-25,273**
		(10,977)
Constant	-0.0963	55,759***
	(0.749)	(9,018)
Observations	464	304
R-squared		0.018

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

6 Conclusion

In conclusion, after applying a novel IV approach that follows Terza (2017) to account for the endogeneity of selection in CBHI and child stunting, we found CBHI reduced 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 a 28.5 percentage point lower probability of stunting at five years. 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 the 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. This raises the concern and the requirement to focus more on girls and women who do not often have equitable access to health services and yet need them often the most. The pathways of impact discussed here at at best, speculative, nonetheless, plausible. There are a couple of outstanding questions which future research might tackle. For instance, how groups function and how social control might enhance positive behaviour change. Moreover, 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.

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Appendix: Supplementary Tables

Table 9: 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 10: First Stage and Reduced form Regressions

	(1) (CBHI Status)		(2) (Stunting prevalence)	
	Coeff	se	Coeff	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) secondary education	−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. * $p< 0.1$, ** $p < 0.05$, *** $p < 0.01$