# Essays on the economics of health-Risk and Insurance

Zelalem Yilma Debebe

This dissertation is part of the Research Programme of CERES, Research School of Resource Studies for Development.

Funded by the Netherlands Organisation for Scientific Research (NWO-WOTRO), grant number W07.45.103.00

MIX
Paper from responsible sources
FSC® C112051
www.fsc.org



Printed in The Netherlands.

ISBN 978-90-6490-052-5

Ipskamp Drukkers B.V.
Josinkmaatweg 43
7545 PS Enschede
Tel.: 0031-(0)53 482 62 62
Fax: 0031-(0)53 482 62 70
http:// www.ipskampdrukkers.nl/

# ESSAYS ON THE ECONOMICS OF HEALTH-RISK AND INSURANCE

## ESSAYS OVER DE ECONOMIE VAN GEZONDHEIDSRISICO EN VERZEKERING

**Thesis**

**to obtain the degree of Doctor from the**
**Erasmus University Rotterdam**
**by command of the Rector Magnificus**
**Professor dr H.A.P Pols**
**and in accordance with the decision of the Doctorate Board**

The public defence shall be held on
**3 December 2015 at 16 hrs**

by

**Zelalem Yilma Debebe**
**born in Asella, Ethiopia**

International
Institute of Social Studies

**Doctoral Committee**

**Promotor**

Prof.dr. A.S. Bedi

**Other Members**

Prof.dr. M. Grimm

Prof.dr. E.K.A. van Doorslaer

Prof.dr. M.P. Pradhan, VU University Amsterdam and University of Amsterdam

**Co-promotor**

Dr. M. Dekker, African Studies Centre Leiden

Dr. R. Sparrow, Australian National University

*To my beloved parents: Beletu Yimer and Yilma Debebe*

# Contents

# List of Tables, Figures and Appendices

# Acronyms

| | |
|---|---|
| ADL | Activities of Daily Living |
| ATT | Average Treatment on the Treated |
| CBHI | Community Based Health Insurance |
| DHS | Demographic and Health Survey |
| DLPH | Days Lost to Poor Health |
| ETB | Ethiopian Birr, the currency of Ethiopia |
| FMoH | Federal Ministry of Health |
| FTN | Factory Treated Nets |
| GH¢ | Ghanaian Cedi, the currency of Ghana |
| GLM | Generalised Linear Model |
| GNI | Gross National Income |
| GPML | Gamma Pseudo Maximum Likelihood |
| ITN | Insecticide Treated Nets |
| LAD | Least Absolute Deviations |
| NHI | National Health Insurance |
| NHIS | National Health Insurance Scheme |
| NN | Nearest Neighbor |
| OLS | Ordinary Least Squares |
| OOP | Out-of-pocket |
| PPP | Purchasing Power Parity |
| PSM | Propensity Score Matching |
| PSNP | Productive Safety Net Programme |
| SAH | Self-assessed Health status |
| SNNPR | Southern Nations, Nationalities, and Peoples' Region |

| | |
|---|---|
| STN | Self Treated Nets |
| UHC | Universal Health Coverage |
| UN | United Nations |
| USA | United States of America |
| USAID | United States Agency for International Development |
| USD | United States Dollar |
| WHO | World Health Organisation |
| 2SLS | Two Stage Least Square |

# Acknowledgements

A number of individuals and organizations have contributed to the successful completion of this PhD thesis. With the risk of unintentionally omitting few names, I would like to take the task of acknowledging those who have been closely supporting this venture.

I literally do not have enough words to express my gratitude to Arjun Bedi and Robert Sparrow, my academic coaches since I first set foot in the Netherlands. While the idea of pursuing a PhD was not an accident, the *where* and *when* came as a surprise. It was back in September 2009 when I was still a master's student that Robert, my MA thesis supervisor, asked me what my plans were after graduation. Who knew the two had a project in mind? Thanks for the opportunity. It has been an immensely elevating experience working with both of you. I very much appreciate your critical remarks and insightful suggestions. Arjun, you have been more than a promotor to me. I have never taken a second thought to knock your door or to send you an e-mail. I am grateful that you believed in me and allowed me to grasp opportunities that came during the course of my studies. I enjoyed every bit of my PhD life to a large extent because of your positive attitude. Now that I am across the Atlantic, I will miss the personal level conversations and our laughter. I could not have asked for more. *Ameseginalehu!*

I am also very grateful to my co-promotor Marleen Dekker for her invaluable comments, encouragement and for promptly responding to my e-mails. To members of my research team and co-authors (Owen O'Donnell, Getnet Alemu, Anagaw Derseh, Ellen van de Poel, Admasu Shiferahu, Luuk van Kempen and Thomas De Hoop) I say, *may we have many more chances to work together*. I thank you for your insightful comments, collaboration and friendship. Owen, I cannot overstate how pleased I am to have worked with you. I learned massively from every single e-mail we exchanged (and there were quite a lot of them). Thank you for your detailed and insightful comments.

I would also like to thank my examiners in the Dissertation Design Seminar and Full Draft Seminar for their critical remarks and useful suggestions: Ellen van de Poel, Igna Bonfrer, Matthias Rieger, Julia Matz and Kim Wilgenburg. The thesis also benefited from comments by participants in various international conferences including the Annual Bank Conference on Africa (Paris), the Nordic Conference on Development Economics (Helsinki), the Annual Bank Conference on Development Economics (Washington DC), the European Development Research Network PhD Workshop (Geneva), the PhD conference at the University of East Anglia (Norwich), the LAGV Conference in Public Economics (Marseille).

The PhD journey had lots of ups and downs. Although I enjoyed most of it, there were moments of frustrations particularly in the upstream of the process. As much as exciting my field work was, there were risks involved in driving more than 200 kilometres per day during survey supervision and in walking through the challenging and yet breathtakingly beautiful landscapes of rural Ethiopia. Thanks to my field work comrades (Tsegaye Moreda (Chise), Addis Abera, Yilma Debebe, Biniyam Yilma and Getnet Alemu) I only have good memories. I enjoyed the laughter, the food and the drinks we shared. Chise, thanks for saving me from that wild dog. It would have been a dreadful health shock. ☺

Next, I would like to extend my gratitude to the Netherlands Organization for Scientific Research (NWO-WOTRO) for funding this research project through grant number W07.45.103.00. As a positive externality of the data collection, the funding has also enabled me to travel to various corners of my country for the first time. The survey benefitted from the institutional support of the Ethiopian Economics Association (EAA) and the Organization for Social Science Research in Eastern and Southern Africa (OSSREA). I would like to thank Degnet, Assefa, Mesfin and Daniel from EEA and Hassen, Belete, Alex, Meski, Pascal, Medhanit, Etalemahu and Mistre from OSSREA. I would also like to acknowledge Abt Associates Inc. and the Ethiopian Health Insurance Agency for providing me with some information.

Needless to say, the thesis would not have been possible without the cooperation of informants, local officers, guides, enumerators and supervisors. I am especially grateful for my respondents who willingly gave their precious time in the hope of a positive change. May everything work in your favor!

I would also like to thank members of the ISS community who have been indirectly supporting this endeavor. From the faculty, I would in particular like to thank John Cameroon, Peter van Bergeijk, and Mansoob Murshed for their follow up and encouragement. To Ank, John, Robin, Eef, Marja, Annet, Martin, Susan, Grace, Dita, Paula and Veronika, thanks for being of service. You truly make ISS a family. The institute has made me grow in several aspects. I have gained from the countless academic debates and workshops held in the building. I was inspired by discussions with fellow PhD colleagues and MA students from all corners of the world. I have great memories of the Butterfly Bar where nothing is left unspoken. Let me dare to make the mistake of naming some frequenters and hosts: Sandy, Dieneke, Chise, Bini, Tefe, Ras, Clau, Lucas, Holger, Elyse, Nick, Juan David, Fasilo, Kenji, Eri, Juan Ca, Liah, Sergio, Sat, Brenda, Caia, Lucia et al.. Butterfliers, your company was instrumental in refreshing my mind. *Muchas Gracias!*

Last but not least, I owe my loving family members (Ababaye, Bele, Netse, Bini and Mita) a million thanks for their encouragement and prayers. Dad, thank you for consistently trying to inspire me through stories of academic achievements. I have lived the past 29 years chasing the dream you authored and I have quite enjoyed the journey. Enatiye, thanks to your prayers the road has been paved. Much love!

# Abstract

Vulnerability to poverty due to various forms of uninsured risks, idiosyncratic or covariate, is common in several developing countries. Existing studies analyse the welfare costs of these adverse events by examining how a particular risk affects the ability of households to maintain consumption levels, often referred to as a test of consumption insurance. Such analyses are used as a justification for both introducing public insurance schemes and setting policy priorities. As a result, policy emphasis has been on designing schemes to deal with covariate risks as compared to health risks.

Set against this background, the first general objective of this thesis is to examine if reliance on tests of consumption insurance may be misleading, in particular, when it comes to ill-health. It approaches this by examining whether ill-health triggers different coping responses compared to other shocks and by investigating the channels of impoverishment due to ill-health. The second general objective of the thesis is to investigate the effectiveness and potential problems of (pilot) health insurance schemes in Sub-Saharan Africa. In addition to a need for credible impact analysis, advocating the role of health insurance in breaking the bridge between ill-health and impoverishment requires an understanding of the potential problems of information asymmetry in insurance markets, namely, adverse selection and ex-ante moral hazard. To achieve these objectives the research presented in this thesis, which consists of five interrelated essays, employs three waves of panel household survey data and event history interviews in rural Ethiopia to (i) examine which shocks trigger which coping responses (ii) identify the channels of impoverishment due to ill-health (iii) evaluate the impact of a recently introduced voluntary Community Based Health Insurance scheme on household economic welfare and (iv) investigate whether it suffers from problems of adverse selection. The last essay uses two waves of panel household survey data and qualitative information from community meetings in rural Ghana to detect if ex-ante moral hazard is a concern in the Ghanaian National Health Insurance.

The analysis presented in this thesis displays clear differences in coping strategies across shock types. Coping with relatively idiosyncratic health shocks is met by reductions in savings, asset sales and especially a far greater reliance on borrowing as compared to other shocks. Reductions in food consumption, a prominent response in the case of natural and economic shocks, is absent in the case of health shocks. A notable aspect of the analysis is that informal safety nets and reliance on friends and family for support, at least in the form of gifts, even in the case of idiosyncratic shocks is virtually non-existent. Focusing on ill-health, the thesis finds evidence of substantial economic risk in terms of increased health expenditure and reduced agricultural productivity. Households cope by resorting to intra-household labor substitution, hiring wage labor, borrowing and depleting assets. While households are able to maintain food consumption, imperfect insurance of non-food consumption is apparent. This effect is larger for households with the lowest ability to self-insure. The thesis argues that the relative insensitivity of food consumption should not be viewed as insurability of food consumption against health shocks but rather as an indication that a reduction in food consumption is not a viable coping response to a health shock as it does not provide cash to meet health care needs. Maintaining current consumption through borrowing and depletion of assets and savings is unlikely to be sustainable in the long term and displays the need for interventions that work towards reducing the financial consequences of ill-health.

After assessing the economic costs of illness in rural Ethiopia, the thesis goes on to evaluate the impact of a pilot voluntary Community-Based Health Insurance (CBHI) scheme launched by the government of Ethiopia in 2011 on various measures of economic welfare. Enrolment is found to lead to a 5 percentage point – or 13 percent – decline in the probability of borrowing and is associated with an increase in household income. There is no evidence that enrolling in the scheme affects consumption or livestock holdings.

Adverse selection is not found to be an issue in the pilot CBHI scheme. Households base expectations regarding future medical expenditure on past spending levels. However, there is high volatility in health expenditure suggesting that the financial viability of the CBHI scheme is unlikely to be affected by adverse selection. Although there is evidence that households are

able to anticipate health expenses to some degree, there is little or no evidence that expectations influence the actual take up of health insurance.

Ex-ante moral hazard (scaling back health-risk prevention efforts after insurance enrolment) is, however, found to be a challenge in the National Health Insurance (NHI) scheme of Ghana. The thesis finds that enrolment in the scheme negatively affects the use of insecticide-treated bed nets (ITNs), the most prominent malaria prevention strategy in malaria endemic areas.

Overall, the findings suggest the following: i) Unlike previous claims, informal safety nets and reliance on friends and family for support, at least in the form of gifts, even in the case of idiosyncratic health-risks is missing. While informal borrowing to deal with idiosyncratic shocks does appear to provide some succour, it is often shunned for various reasons. This suggests a potentially important role for formal protection systems. ii) Analysis of the conduits of impoverishment due to ill-health suggests that the adverse consequences might be shrouded by coping responses that pass the immediate costs of ill-health to future periods (e.g. borrowing and asset sales). The insensitivity of total consumption and food consumption to ill-health suggest that perhaps insurance schemes will not affect these outcomes at least in the short-run. The impact analysis also supports this claim. iii) Although there is evidence supporting the ability of households to anticipate health care expenditure, there is little or no evidence that expectations influence the decision to take out health insurance. Even if this was the case, realization of expectations is far from perfect, suggesting that the financial viability of the scheme is unlikely to be heavily affected by adverse selection. iv) Analysis of the Ghanaian National Health Insurance scheme shows that there is a need to tackle changes in risk-taking behaviour which may be triggered by health insurance. While the introduction of co-payments is the most straight forward policy implication, it is likely to compromise the move towards Universal Health Coverage. Complementary health education and awareness programs that highlight the health effects of reduction in one's immunity as a result of frequent illness could be alternatives.

*Essays over de economie van gezondheidsrisico en verzekering*

# Samenvatting

Kwetsbaarheid voor armoede als gevolg van verschillende vormen van op zichzelf staande en samenhangende onverzekerde risico's komt veel voor in een aantal ontwikkelingslanden. In bestaand onderzoek worden de welzijnskosten van deze negatieve gebeurtenissen geanalyseerd door het effect van een bepaald risico op het vermogen van huishoudens om het consumptieniveau te handhaven te onderzoeken. Dit wordt vaak omschreven als een toets van consumptieverzekering. Dergelijke analyses worden gebruikt als een rechtvaardiging van zowel de introductie van volksverzekeringen als het stellen van prioriteiten voor beleid. Hierdoor ligt de nadruk op het ontwerpen van verzekeringsstelsels voor samenhangende risico's in tegenstelling tot gezondheidsrisico's.

Tegen deze achtergrond is het eerste algemene doel van dit proefschrift om te onderzoeken of het misleidend kan zijn om te vertrouwen op toetsen van consumptieverzekering, met name wanneer het gaat om slechte gezondheid. Hiertoe is onderzocht of slechte gezondheid andere copingstrategieën oproept dan andere tegenslagen en via welke wegen slechte gezondheid leidt tot verarming. Het tweede algemene doel van het proefschrift is om de effectiviteit en de potentiële problemen van (proeven met) ziektekostenverzekeringen in Afrika ten zuiden van de Sahara te onderzoeken. Naast de behoefte aan een geloofwaardige analyse van de impact, vereist een pleidooi voor de rol van ziektekostenverzekeringen bij het doorbreken van het verband tussen slechte gezondheid en verarming een begrip van de potentiële problemen van informatie-asymmetrie in verzekeringsmarkten, namelijk negatieve selectie en moreel risico ex ante. Om deze doelen te bereiken is in dit onderzoek, dat bestaat uit vijf gerelateerde essays, gebruikgemaakt van een panelonderzoek onder huishoudens in drie rondes en zijn interviews op het platteland in Ethiopië gehouden om (i) te onderzoeken welke tegenslagen welke copingstrategieën uitlokken; (ii) na te gaan via welke wegen slechte gezondheid leidt tot verarming (iii) de invloed van een onlangs geïntroduceerde vrijwillige Gemeenschapsgerichte Ziektekostenverzekering op het economisch welzijn van huishoudens te evalueren en (iv) te onderzoeken of daarbij sprake is van negatieve selectie. Het laatste essay is gebaseerd op enquêtes die zijn afgenomen in twee rondes van panelonderzoek onder huishoudens en op kwalitatieve informatie uit dorpsbijeenkomsten op het platteland in Ghana om erachter te komen of moreel risico ex ante een rol speelt in de Ghanese Nationale Ziektekostenverzekering.

Uit het onderzoek in dit proefschrift blijkt dat er duidelijke verschillen zijn in copingstrategieën bij verschillende soorten tegenslagen. In vergelijking met tegenslagen die minder persoonlijk van aard zijn, spreken mensen bij gezondheidsproblemen eerder hun spaargeld aan of verkopen ze bezittingen, en sluiten ze vooral vaker leningen af. Een van de meest typerende reacties op natuurrampen en economische crises, een afname van de voedselconsumptie, komt niet voor bij gezondheidsproblemen. Een opvallend aspect van het onderzoek is dat er vrijwel geen sprake is van informele vangnetten en hulp van vrienden en familie, in ieder geval niet als vriendendienst, zelfs in geval van persoonlijke tegenslagen. Uit deze studie blijkt dat slechte gezondheid een aanzienlijk economisch risico met zich meebrengt in termen van hogere ziektekosten en verminderde landbouwproductiviteit. Huishoudens gaan hiermee om door een beroep te doen op vervangende arbeidskrachten binnen het huishouden, betaalde arbeidskrachten in te huren, te lenen en bezittingen te gelde te maken. Terwijl de voedselconsumptie van huishoudens op peil blijft, blijkt de consumptie van andere goederen onvoldoende verzekerd te zijn. Dit effect is groter voor huishoudens die het slechtst in staat zijn zichzelf te verzekeren. In dit proefschrift wordt betoogd dat de relatieve onaantastbaarheid van voedselconsumptie niet opgevat moet worden als de verzekerbaarheid van voedselconsumptie tegen gezondheidsproblemen, maar eerder als indicatie dat een verminderde voedselconsumptie geen werkbare copingstrategie is bij gezondheidsproblemen, omdat het geen geld oplevert om ziektekosten te dekken. Het handhaven van het huidige consumptieniveau door te lenen, bezittingen te verkopen en op spaargeld in te teren is op de lange termijn waarschijnlijk onhoudbaar en wijst op de behoefte aan interventies die gericht zijn op het verzachten van de financiële consequenties van slechte gezondheid.

In dit proefschrift wordt een schatting gemaakt van de economische kosten van ziekte op het platteland in Ethiopië, waarna een evaluatie volgt van het effect van een door de Ethiopische overheid in 2011 uitgevoerde proef met een vrijwillige Gemeenschapsgerichte Ziektekostenverzekering (Community-Based Health Insurance; CBHI) op verschillende maten van economisch welzijn. Deelname bleek te leiden tot een afname van 5 procentpunt – of 13 procent – in de kans op lenen en hangt samen met een inkomensverhoging van huishoudens. Er zijn geen aanwijzingen dat deelname aan de verzekering invloed heeft op de consumptie of veehouderij.

Negatieve selectie blijkt geen rol te spelen in de proef met de CBHI. Huishoudens baseren verwachtingen over toekomstige ziektekosten op uitgaven in het verleden. Ziektekosten variëren echter sterk, waardoor het onwaarschijnlijk is dat de financiële uitvoerbaarheid van het CBHI-plan gehinderd wordt door negatieve selectie. Hoewel er aanwijzingen zijn dat huishoudens ziektekosten tot op zekere hoogte kunnen voorzien, zijn er weinig tot geen aanwijzingen dat verwachtingen van invloed zijn op feitelijke deelname aan een ziektekostenverzekering.

Moreel risico ex ante (afname van preventieve gezondheidsmaatregelen na het afsluiten van de verzekering) blijkt echter wel een probleem te vormen bij de Ghanese Nationale Ziektekostenverzekering (National Health Insurance; NHI). Uit het onderzoek blijkt dat deelname aan de verzekering een negatief effect heeft op het gebruik van met insecticiden behandelde muskietennetten, de belangrijkste methode om malaria te voorkomen in gebieden waar malaria endemisch is.

Op grond van de onderzoeksresultaten kunnen de volgende conclusies worden getrokken: i) In tegenstelling tot eerdere bevindingen blijkt het te ontbreken aan informele vangnetten en hulp van vrienden en familie, in ieder geval voor zover die als vriendendienst wordt geboden; zelfs in geval van persoonlijke gezondheidsrisico's. Hoewel informele leningen om persoonlijke tegenslagen op te vangen wel enig soelaas lijken te bieden, wordt deze optie om verschillende redenen vaak niet gekozen. Dit wijst op een potentieel belangrijke rol voor formele beschermingssystemen. ii) Uit een analyse van de wegen waarlangs slechte gezondheid tot verarming leidt, komt naar voren dat de negatieve gevolgen wellicht verhuld worden door copingstrategieën waarmee de onmiddellijke kosten van slechte gezondheid worden doorgeschoven naar de toekomst (bijvoorbeeld leningen en de verkoop van bezittingen). Het gegeven dat slechte gezondheid geen effect heeft op de totale consumptie en de voedselconsumptie wijst erop dat verzekeringsstelsels althans op de korte termijn mogelijk geen gevolgen hebben voor deze factoren. Deze conclusie wordt ook gesteund door de impactanalyse. iii) Hoewel er aanwijzingen zijn dat huishoudens in staat zijn om ziektekosten te voorzien, zijn er weinig tot geen aanwijzingen dat verwachtingen van invloed zijn op de beslissing om een ziektekostenverzekering af te sluiten. En zelfs al was dit het geval, dan nog komen verwachtingen vaak niet uit, waardoor de kans dat de financiële uitvoerbaarheid van het stelsel gehinderd wordt door negatieve selectie waarschijnlijk klein is. iv) Uit het onderzoek naar de Ghanese Nationale Ziektekostenverzekering blijkt de noodzaak om in te spelen op veranderingen in risicogedrag die het gevolg kunnen zijn van een ziektekostenverzekering. De invoering van een eigen bijdrage is weliswaar de duidelijkste beleidsimplicatie, maar dit gaat waarschijnlijk niet goed samen met het streven naar een universele dekking van ziektekosten. Aanvullend gezondheidsonderwijs en bewustmakingsprogramma's waarin gezondheidseffecten zoals een vermindering van de weerstand ten gevolge van vaak ziek zijn benadrukt worden, zouden alternatieven kunnen zijn.

# 1 Introduction

Households across the developing world are vulnerable to poverty due to various forms of uninsured risks, idiosyncratic or covariate (Gertler and Gruber 2002, Dercon et al. 2005, Wagstaff 2007, Hoddinot 2006, Islam and Maitra 2012, Sparrow et al. 2014). One of these sources of uninsured risk is ill-health, which involves financial risk due to the direct and indirect costs of medical care and forgone income. The welfare implication of these adverse events is often examined by assessing the extent to which a particular risk affects the ability of households to maintain consumption levels, often referred to as a test of consumption insurance (e.g. Gertler and Gruber 2002, Asfaw and Von Braun 2004, De Weerdt and Dercon 2006, Wagstaff 2007, Gertler et al. 2009, Davies 2010). Justifications for introducing social insurance schemes and setting policy priorities often rely on tests of consumption insurance (e.g. Morduch 1995, Gertler and Gruber 2002, Asfaw and Von Braun 2004). As a result, policy emphasis has been on designing schemes to deal with covariate risks as compared to health risks.

However, recently, the World Health Organization and the World Bank have argued in favour of the introduction of various forms of prepayment methods in order to prevent the impoverishing effects of dealing with out-of-pocket payments for health care and the deleterious effects of prolonged untreated illness (WHO and World Bank 2013). In part, the increasing proliferation of health insurance schemes in Sub-Saharan Africa (SSA) emanates from such concerns. The recent introduction of a pilot voluntary Community Based Health Insurance (CBHI) scheme in rural Ethiopia and Ghana's National Health Insurance (NHI) scheme are two examples in this regard.[1,2] Both aim at providing financial protection against illness related expenses and increasing access to modern healthcare (Mensah et al. 2010, USAID 2011).

Since July 2011, the Ethiopian CBHI, which is meant for households living in rural areas and for those employed in the informal sector, has been operating in thirteen districts (woredas) located in four regions (Amhara, Oromiya, SNNPR and Tigray) of the country. The eventual aim is to launch a nation-wide rollout of this pilot scheme.[3,4] This demand side intervention was preceded by the establishment of health posts and deployment of health extension workers to provide outreach services (FMoH 2005). The Ghanaian NHI scheme was introduced in 2003 to replace the cash-and-carry system. It covers both the formal and the informal sectors.

In addition to the need for credible impact analyses of such (pilot) schemes, advocating the role of health insurance in breaking the bridge between ill-health and impoverishment requires an understanding of the potential problems of information asymmetry in insurance markets, namely adverse selection and ex-ante moral hazard (scaling back prevention efforts after insurance).[5] Health insurance might impact a household's economic welfare by serving as a risk management tool (e.g. reducing inefficient precautionary savings) and by altering the mix of ex-post coping responses adopted by households (World Bank 2014). While there is evidence on the impact of such interventions (see review by Mebratie et al. 2013a) on access to modern health care, there is little evidence on the effect of such schemes on the economic welfare of poor households. Moreover, while both problems of adverse selection and ex-ante moral hazard are well-established in economic theory, convincing empirical studies which provide evidence of adverse selection and moral hazard especially in developing countries is limited.

Set against this background, the first general objective of this thesis is to examine if reliance on tests of consumption insurance may be misleading, in particular, when it comes to ill-health. It approaches this by examining whether ill-health triggers different coping responses compared to other shocks[6] and by investigating the channels of impoverishment due to ill-health.[7] The second general objective of the thesis is to investigate the effectiveness and potential problems of (pilot) health insurance schemes in Sub-Saharan Africa. To achieve these objectives the thesis consists of five interrelated essays that aim to (i) examine which shocks trigger which coping responses (ii) identify the channels of impoverishment due to ill-health (iii) evaluate the impact of the Ethiopian CBHI on household economic welfare (iv) investigate whether it suffers from problems of adverse selection (v) detect if ex-ante moral hazard is a concern in the Ghanaian National Health Insurance.

The essays rely on panel data and qualitative data collection efforts which were undertaken in rural Ethiopia and Ghana. For the essays based on Ethiopia, the thesis draws on three-rounds of panel data collected in March-April of 2011, 2012 and 2013. The first round was collected a few months before the launch of the CBHI scheme and serves as a baseline. Sixteen districts located across four main regions of the country (Amhara, Oromiya, Tigray and SNNPR) are included in the survey. Within the districts a two stage sampling design, randomly sampling villages (six from each district) and the households (17 from each village) is used. The total sample size in the first round is 1,632 households comprising 9,455 individuals, of which 98 and 97 percent were successfully re-surveyed in 2012 and 2013. In addition to the household surveys, in January-February 2013, after analysing the household survey data, event history interviews were conducted with purposively selected households who had also been interviewed for the household survey. The thesis relies on 42 such in-depth interviews with household heads.

The essay on Ghana relies on two rounds of panel data gathered from 400 households who were surveyed in September 2007 and 2009.[8] The surveyed households are spread over eleven different communities, seven of which are located in Asutifi district and four in the adjacent Asunafo district of the Brong Ahafo region. Within these communities, a sample of households, proportional to the community's population size, was randomly drawn. In addition, in June 2010 a series of participatory debriefing sessions on the outcomes of the study were organized in five of the surveyed communities.

A more detailed description of the five essays is presented below. The first essay employs the baseline household survey data and event history interviews conducted in rural Ethiopia to investigate which shocks trigger which coping responses and why. It distinguishes between health and non-health shocks and establishes that coping responses in the case of health shocks are different as compared to non-health shocks. The analysis provides insights on why previous studies have reported that consumption is less sensitive to health shocks as compared to non-health shocks. The conclusion of this essay lays the groundwork for the subsequent essay.

The second essay employs all three survey waves and event history interviews to examine the channels of impoverishment due to ill-health. It examines the immediate effects of a variety of ill-health measures on health expenditure and labor supply, the subsequent household coping responses, and finally the effect on household income and consumption. By providing a comprehensive understanding of the economic costs of illness, the essay displays the need for interventions that work towards reducing the financial consequences of ill-health.

The third essay assesses the impact of CBHI on household consumption, income, indebtedness and livestock holdings. The availability of a baseline and two follow up surveys offers an opportunity to conduct a credible impact evaluation and provide empirical evidence on the potential role that may be played by such schemes on household economic welfare. In doing so, the essay goes beyond the conventional emphasis on evaluating the impact of such schemes on access to healthcare access. Results suggest that the main benefit of the scheme is its effect on reducing the need to borrow and thereby potentially reducing vulnerability to other forms of shocks.

The fourth essay employs a novel approach to investigate the prevalence of adverse selection in CBHI. Subjective probabilities of medical expenditures are elicited from respondents, and after assessing the validity of such data obtained from poor and less-educated individuals the essay examines whether or not expectations depend on past realized expenditure, the extent to which expectations materialise and how far households' expectations influence the decision to enrol in CBHI. The overall analysis suggests that adverse selection is unlikely to be of great concern in the case of the Ethiopian CBHI.

The last essay investigates incentive problems in the Ghanaian National Health Insurance (NHI), specifically whether or not enrolment in the NHI scheme leads to a decline in malaria prevention efforts (ex-ante moral hazard).[9] It exploits the panel nature of the household survey to test whether enrolment negatively affects ownership and use of insecticide-treated bed nets. Results suggest the presence of ex-ante moral hazard.

The concluding chapter of the thesis summarizes the key findings and considers policy implications.

## Notes

[1] Ethiopia is the second most populous country in Africa with 94.1 million people in 2013. The country is categorized as a developing, low income country with GNI per capita of $470 in 2013. Despite impressive economic growth in recent years (10.4% in 2013), poverty head count ratio at national poverty lines amounts to about one-third (29.6% in 2011) of the population (World Bank 2013) while 88% of the population is affected by multidimensional poverty according to the UN's Human Development Report 2014. In 2013, the country ranked 173rd out of 187 countries in the Human Development Index. With high infant, under-five and maternal mortality, life expectancy at birth is about 63 years (UN 2014).

[2] Ghana is a lower middle income country with GNI per capita of $1770 in 2013. Although it recently departed the World Banks's low income category, poverty head count ratio at national poverty lines amounts to about one-fourth (24.2 in 2012) of the population (World Bank 2013).

[3] The scheme has recently been extended to 161 districts for further testing. The Ministry also plans to start a mandatory social health insurance for the formal sector as part of its health care financing strategy. Until recently, thirty-seven percent of the national health expenditure (in 2007/08) was financed from out-of-pocket payments (FMoH 2010).

[4] Woreda is an administrative unit. The country administration is divided into regions, regions into zones, zones into woredas, woredas into kebeles and in rural areas these kebeles are further divided in to gots.

[5] Both problems of information asymmetry could pose a potential burden for a health care system and, in the longer term, could be a hurdle for achieving UHC.

[6] Risk refers to the possibility of loss while shock refers to the realizations of this adverse possibility. Dercon et al. (2005) defines shocks as events that may lead to economic difficulties such as loss of household income, loss of productive assets, unexpected expenditure and/or reduction in consumption.

[7] In fact, analysis of the channels of impoverishment is becoming increasingly common (see for example, Gertler and Gruber 2002, Wagstaff 2007, Islam and Maitra 2010, Sparrow et al. 2014) although the focus is still on whether consumption is insured or not.

[8] Seven households could not be traced in the second round and were replaced by neighbouring households.

[9] Despite various interventions, malaria is still Ghana's leading cause of mortality and morbidity and imposes a large burden on its health care system.

# 2 Coping with Shocks in Rural Ethiopia[1]


## Abstract

Based on household survey data and event history interviews undertaken in a highly shock prone country, this paper investigates which shocks trigger which coping responses and why. We find clear differences in terms of coping strategies across shock types. The two relatively covariate shocks, that is, economic and natural shocks are more likely to trigger reductions in savings and in food consumption while the sale of assets and borrowing is less common. Coping with relatively idiosyncratic health shocks is met by reductions in savings, asset sales and especially a far greater reliance on borrowing as compared to other shocks. Reductions in food consumption, a prominent response in the case of natural and economic shocks is notably absent in the case of health shocks. Across all shock types, households do not rely on gifts from family and friends or on enhancing their labour supply as coping approaches. The relative insensitivity of food consumption to health shocks based on the shocks-coping analysis presented here is consistent with existing work which examines consumption insurance. However, our analysis leads to a different interpretation. We argue that this insensitivity should not be viewed as insurability of food consumption against health shocks but rather as an indication that a reduction in food consumption is not a viable coping response to a health shock as it does not provide cash to meet health care needs.


## 2.1 Introduction

Rural households in developing countries such as Ethiopia confront a variety of risks and shocks which may render them vulnerable to severe economic deprivations. Acquiring a greater understanding of the risks, vulnerabilities and coping mechanisms available to deal with the range of shocks faced by households is essential in order to prioritize and design appropriate social safety nets.[2] In the absence of formal protection systems, the ability of households to protect themselves is influenced by the frequency, scope and intensity of shocks. Theoretically, it is for example expected that households are more likely to be able to insure themselves against relatively idiosyncratic shocks by drawing on informal risk-sharing networks, as compared to common shocks that also affect other members of a village and thus render the risk pool weaker. If some shocks are indeed more difficult to insure against than others, then specific policies designed to deal with less-insurable shocks are likely to be more beneficial in terms of alleviating economic hardship.

Recognizing the role played by a range of natural, health and economic shocks in perpetuating poverty, a relatively recent strand of development research has been concerned with determining the effect of health and other shocks on consumption, income and labour supply. Typically such studies examine the effect of a single shock on a key welfare measure, usually consumption, and focus on identifying the effect of past shocks on current household consumption.[3]

While results vary across countries, in the Ethiopian context, Asfaw and von Braun (2004) conclude that food consumption is protected against the illness of the household head while non-food consumption is not insured. In their multi-shock analysis on Ethiopia, Dercon et al. (2005) show that droughts occurring in the five years before the survey reduce total annual per capita consumption by 20 per cent while illnesses reduce consumption by 9 per cent. Before concluding that the consequences of droughts are worse than illnesses or that health shocks do not affect food consumption, it is important to consider whether the coping responses to different types of shocks has a bearing on such outcomes. In the context of a formal test of consumption insurance, Chetty and Looney (2006) argue that insurability of consumption should be interpreted with caution and that it is important to consider what underlies such a result. Drawing the conclusion that households are able to protect (current) consumption against a certain shock without considering the manner in which such protection has been achieved may be misleading especially if such protection has come at the cost of borrowing or the sale of productive assets, with possible consequences for future consumption.

Obtaining a deeper understanding of household ability to respond to and to insure against different types of shocks thus not only requires a multi-shock analysis but also an examination of coping mechanisms. While there are papers that have adopted such a multi-shock approach the bulk of the work adopts a partial approach and analyses the effects of a single shock or a limited set of shocks. Studies that have analysed the incidence, distribution and welfare implications of a broad range of shocks include Wagstaff and Lindelow (2010), Heltberg and Lund (2009) and Dercon et al. (2005). Such comparative studies are informative and have challenged the conventional wisdom that covariate shocks such as crop failure are more difficult to deal with as compared to idiosyncratic shocks like illnesses.

Motivated by the idea that the apparent insurability of consumption for certain shocks vis-à-vis others may be driven by different coping responses to different types of shocks, this paper uses purposively collected household data and event history interviews conducted in a highly shock prone country to investigate a relatively neglected question, that is, which shocks trigger which coping responses and why. Similar to Wagstaff and Lindelow (2010) and Heltberg and Lund (2009), the paper relies on cross-section data and a retrospective shock module to analyse the shock-coping strategy link. The paper adds to the scant literature on multi-shock comparative studies and is timely from a policy perspective as the Ethiopian government intends to upscale a community based health insurance (CBHI) scheme that was piloted in 2011.

To preview our results, unlike recent multi-shock studies by Wagstaff and Lindelow (2010) and Heltberg and Lund (2009), we find that health shocks do not dominate in terms of frequency, natural shocks do. Health shocks are more likely to trigger borrowing and selling of assets as compared to non-health shocks while natural shocks stand out in triggering a reduction in consumption and dissaving. Economic shocks and crime/conflict/family shocks do not seem to induce an active response. The differential coping response to health and natural shocks highlights the different consumption effects associated with the two types of shocks and the underlying reasons for the apparent insurability of health shocks.

The paper unfolds by providing in section 2.2 a description of the data and the sampling design. Section 2.3 discusses methods. Section

2.4 examines the frequency of shocks, their scope and distribution and presents a bivariate and a multivariate analysis of which shocks trigger which coping responses. Section 2.5 contains concluding observations.

## 2.2 Data and Sampling

This study is based on a household survey which covers four regions of Ethiopia (Tigray, Amhara, Oromiya, and SNNPR) and in-depth interviews with a selection of the households who were also included in the survey. From each of these regions, which together account for about 86 percent of the country's population (Population Census Commission, 2008) four districts were purposively selected and within each district 6 kebeles (peasant associations or villages) were randomly drawn.[4] In each of the 96 kebeles, 17 households were randomly surveyed yielding a total of 1,632 households comprising 9,455 individuals.

The survey was canvassed between March and April 2011 and contains information on a variety of individual and household socio-economic attributes such as consumption expenditure, assets, household demographics, employment and household health conditions. The survey includes an extensive module to explore the comparative effect of shocks. The shock module asks households about their experience of unexpected events in the year before the survey. These include health related events (illness, death or disability), natural events (flood, storm, drought, untimely rain, insect damage, fire, frost), economic events (death of livestock, loss of equipment, unemployment, a decline in output price[5]) and crime/conflict/family related events (conflict over land or water, divorce, theft of crops and theft of livestock). In addition, the survey enquires i) how strongly households are affected by these events, ii) how many households in the village are affected by the events and iii) which are the three most important coping responses used (if any).[6]

In order to acquire a deeper understanding of why particular coping responses were chosen (or not) in response to a certain shock, in January-February 2013, after analysing the household survey data, event history interviews were conducted with purposively selected households who had also been interviewed for the household survey.[7] From each of the four regions, a district with a relatively high burden of shocks was selected and within each of these four districts, households were sampled based on the reported incidence and the severity of shocks they had experienced.[8] A total of 42 households were interviewed.

## 2.3 Methodological approach

### 2.3.1 Incidence, scope and distribution of shocks

We commence our analysis by providing an assessment of the incidence, scope (covariate or idiosyncratic) and distribution of shocks (who experiences shocks). To enhance tractability we categorize information on the 21 different events (or sub-types) into four major shock types: health, natural, economic and crime/conflict/family related shocks.

To examine whether a particular shock is idiosyncratic or covariate we follow Dercon et al. (2005) and assess responses to the question whether an event affected only the respondent household or other households in the same kebele as well.[9] Even though it is hard to label a shock as purely idiosyncratic or purely covariate, as many shocks lie in between, we consider a shock as idiosyncratic if it is reported to have affected only that household and covariate if it affects at least some other households in the kebele.

To examine the household characteristics that are related to the probability of facing shocks, we estimate probit models for each of the shock types on a vector of covariates, which includes measures of economic status, human capital, demographics, religion and regional dummies. The measure of economic status is based on an asset index constructed on the basis of a principal component analysis using 68 items that include housing features, land size, various consumption assets, farm equipment and livestock.[10] Human capital is measured by education of the household head, the demographic variables include household size, age and sex of head and share of males and females in the household.

### 2.3.2 Shocks and coping

Coping, defined as actions undertaken by a household to accommodate the effect of a shock, is divided into six categories plus the option that the household did not adopt any active coping response. These six categories include the use of savings, reducing food consumption, selling assets (including food stocks), borrowing (from relatives, formal sources, neighbours, money lenders, and funeral and credit associations), receiving gifts (in cash or in kind from informal groups, neighbours or the government) and labour supply based strategies (increasing own labour input, hiring in, sending out family members outside the kebele, working off-farm). The categories borrowing and receiving gifts can be considered as external coping strategies while the remainder may be considered as internal (to the household) coping strategies.

Using information from the survey as well as the in-depth interviews, we examine which shocks trigger which coping responses and whether coping responses vary by the severity of a specific shock. We treat the probability of adopting a coping strategy as a function of the four shock types and a range of household and village characteristics,

$$\text{prob}(CS_i^m = 1) = F\left(\alpha + S_i{}'\beta + X_i{}'\phi + \varepsilon_{i.}\right). \tag{2.1}$$

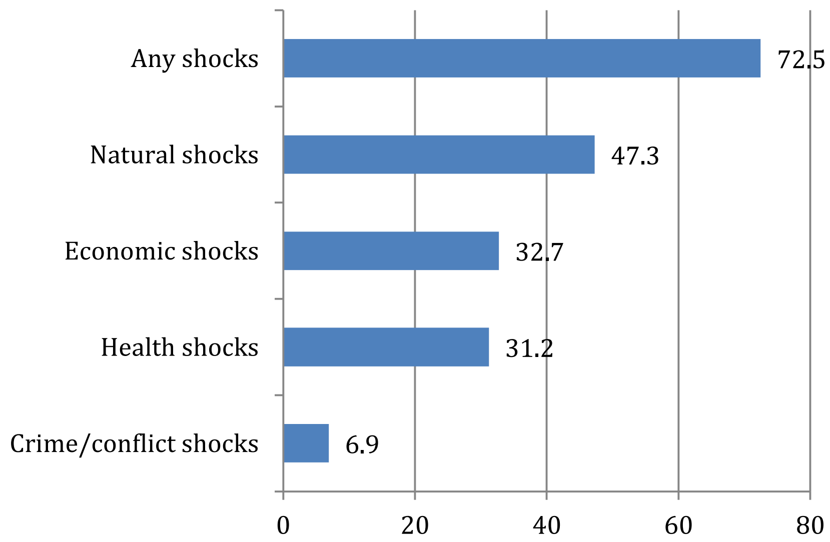
We estimate a series of probit models for each coping response $m$ that household $i$ may adopt. Our main interest centres on the vector of coefficients $\beta$ for shock variables S. The specification further controls for an array of household and community characteristics X, which includes measures of i) economic status, ii) human capital iii) social capital iv) demographic features v) religion of the head and vi) regional dummies (see Appendix Table A2.1 and A2.2 for details). A clear limitation of our analysis is that while (2.1) controls for a wide range of covariates, the error term $\varepsilon$ might still include unobserved household-specific heterogeneity that may influence both the incidence of shocks and the choice of coping strategy, thereby potentially confounding the analysis. While we cannot deal with this issue directly, as we only have access to cross-section data, we do examine the sensitivity of the estimates by estimating a number of alternative specifications. These include estimates which control for Kebele (lowest administrative unit) fixed effects to control for unobserved heterogeneity and seemingly unrelated (linear) regressions which allow the error terms for the different coping responses to be correlated.

## 2.4 Estimates

### 2.4.1 Frequency and scope of shocks

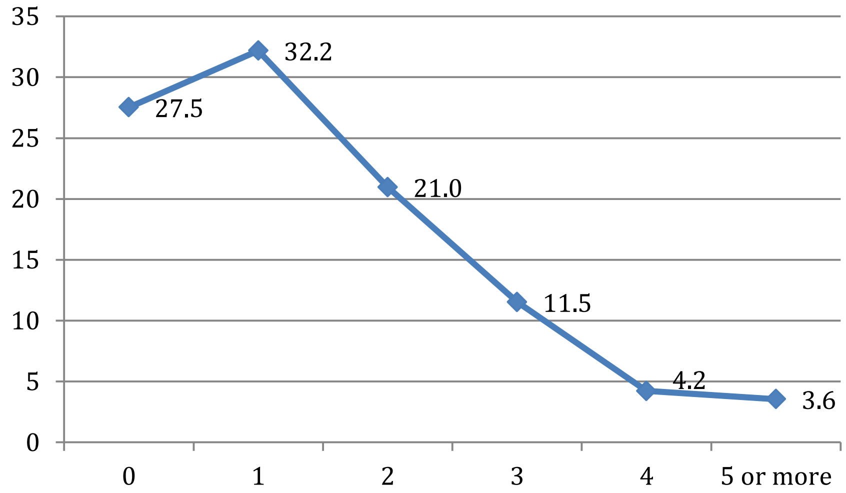
Figure 2.1 presents the frequency of shocks experienced by households. Not unexpectedly, we find that shocks are an important part of the life of rural households. Almost three quarters of our sampled households have faced at least one type of shock in the past 12 months, which is high.[11] Many of these households have experienced multiple shocks (Figure 2.2). A third of the sample reported just one shock, while 21 and 11 per cent of households have faced two and three shocks, respectively. A small percentage of households have faced at least five shocks (4 per cent).

***Figure 2.1***
*Incidence of shocks (per cent of households)*




Unlike Heltberg and Lund (2009) and Wagstaff and Lindelow (2010), health shocks do not appear to dominate in terms of frequency (see Figure 2.1).[12] The most frequent are natural shocks (47%), while health and economic shocks each affect almost one third of the sampled households. Shocks related to crime/conflict/family are not as frequent and are experienced by 7 per cent of the sampled households.

***Figure 2.2***
*Number of shocks experienced (per cent of households)*




In terms of the scope of shocks (see Table 2.1), we find that health shocks are the most idiosyncratic of all shock types as about 84 per cent of such shocks are reported to have affected only the household itself. This is expected in cases where the health shock is not an epidemic. Natural shocks show a strong covariate pattern, with more than 92 per cent having effects beyond the household. Economic shocks may also be classified as partially covariate as the majority of such shocks (66%) tend to affect more than the household in question. Crime/conflict/family shocks, on the other hand, seem relatively idiosyncratic as 74 per cent of such shocks affect only the reporting household.

As discussed in the introduction, the distinction between covariate and idiosyncratic shocks has implications for the portfolio of available coping strategies. Theoretically, households should be able to draw on informal risk-sharing networks (borrowing, social support and use of labour based strategies) to deal with health and crime/conflict/family related shocks as these are relatively idiosyncratic. In contrast, for relatively covariate shocks (natural and economic) of similar severity in terms of cost to an individual household, the potential to access informal support (or credit) or enhance labour supply may be reduced if the local community is also affected by the shock.[13] The link between shock type, the available coping responses and the validity of the theoretically expected ability to cope with some shocks versus others is explored in more detail in the next section.

**Table 2.1**
*Scope of shocks*

| | *Affected only my household* | *Affected some households in this Kebele* | *Affected all households in this Kebele* | *Affected this and nearby Kebeles* | *Affected areas beyond this Kebele* |
|---|---|---|---|---|---|
| Health | 83.89 | 14.04 | 1.69 | 0.00 | 0.00 |
| Natural | 7.37 | 29.65 | 38.63 | 20.93 | 3.32 |
| Economic | 34.26 | 12.89 | 30.67 | 17.46 | 4.40 |
| Crime/ conflict/family | 73.95 | 23.53 | 2.52 | 0.00 | 0.00 |

*Notes: All figures are in percentages*

## 2.4.2 Distribution of shocks

Probit estimates (marginal effects) of the probability of experiencing each of the four shock types as a function of various traits are provided in Table 2.2.[14] With regard to household wealth status, as reflected in the asset index, we find that households in the second and third quintiles are 7 to 9 percentage points less likely to report a health shock as compared to the poorest quintile while the difference is not statistically significant for the other quintiles. The wealth gradient for economic shocks is also not systematically significant with only the second quintile having a significantly higher chance of reporting an economic shock as compared to the poorest quintile. The case of a natural shock is mixed. While households in the second and third quintile have a higher probability of reporting natural shocks, those in the richest quintile are less likely to report natural shocks. The latter could reflect the fact that the richest households live in areas less prone to natural disasters such as floods. We do not find any statistically significant wealth gradient for the case of crime/conflict/family shock.

Turning to measures of human capital, consistent with the positive association between education and health, households where heads have informal education are about 13 percentage points less likely to report health shocks as compared to households where heads have no education. For higher education levels this difference is both statistically and economically insignificant perhaps reflecting a non-linear link between awareness of health conditions and the reporting of health shocks. The association between economic shocks and educational level of the household head appears to have a positive gradient. However, the only statistically significant difference is between households whose heads have primary education as compared to those with no education (about 7 percentage points). There is no particular pattern between human capital measures and natural and crime/conflict/family shocks.

Larger families are more likely to report having experienced a health, economic and natural shock. Perhaps this is not surprising as larger families, simply due to their size, may be more likely to experience these shocks. For the most part, the gender of the household head and gender composition of the household does not have a bearing on the probability of experiencing shocks.

There is a clear link between geographical location and the prevalence of shocks. For instance, households in the Amhara region seem to be far more vulnerable to health, natural and crime/conflict/family shocks as compared to households in Tigray. Households in SNNPR are more likely to report health, economic and crime/conflict/family shocks as compared to their counterparts in Tigray. While households residing in Oromiya are more likely to experience health and crime/conflict/family shocks as compared to their counterparts in Tigray, the differences are not as pronounced.

Overall, the gist of the analysis is that while the link between the various traits and the shock variables varies across shocks, it is clear that shocks are not uniformly distributed. There are differences across geographical locations, levels of economic status and human capital endowment and there is a need to control for such traits in equation (2.1).

***Table 2.2***
*Probability of experiencing a shock*

| | | *Health* | *Economic* | *Natural* | *Crime/conflict/family* |
|---|---|---|---|---|---|
| Economic status | Asset quintile 2 | -0.0699* | 0.0846* | 0.0957** | -0.00228 |
| | | (0.0368) | (0.0484) | (0.0461) | (0.0165) |
| | Asset quintile 3 | -0.0908** | 0.0758 | 0.105** | -0.0108 |
| | | (0.0384) | (0.0491) | (0.0514) | (0.0160) |
| | Asset quintile 4 | -0.0592 | 0.0762 | 0.0550 | 0.00622 |
| | | (0.0361) | (0.0520) | (0.0500) | (0.0167) |
| | Asset quintile 5 | -0.0574 | 0.0467 | -0.0538 | 0.00337 |
| | | (0.0437) | (0.0615) | (0.0583) | (0.0193) |
| Human capital (Head's education) | Informal educ. | -0.124*** | 0.0275 | 0.00891 | -0.0160 |
| | | (0.0303) | (0.0401) | (0.0481) | (0.0127) |
| | Primary educ. | -0.0165 | 0.0699** | 0.0435 | -0.0134 |
| | | (0.0299) | (0.0343) | (0.0313) | (0.0130) |
| | Secondary (+) educ. | 0.0244 | 0.0994 | -0.0786 | -0.00296 |
| | | (0.0520) | (0.0699) | (0.0840) | (0.0273) |
| Demographics | Household size | 0.0236*** | 0.0207*** | 0.0180** | -0.00495* |
| | | (0.00673) | (0.00676) | (0.00800) | (0.00300) |
| | Age of head | 0.000548 | 0.000479 | -0.000532 | -0.00137*** |
| | | (0.000861) | (0.00110) | (0.00113) | (0.000481) |
| | Head sex (male=1) | 0.0353 | -0.00234 | 0.0524 | -0.0132 |
| | | (0.0393) | (0.0428) | (0.0436) | (0.0202) |
| | Male share | 0.00496 | -0.0933 | -0.120* | 0.00987 |
| | | (0.0657) | (0.0655) | (0.0712) | (0.0272) |
| | Adult share | 0.156** | 0.128** | 0.00389 | -0.0339 |
| | | (0.0638) | (0.0643) | (0.0745) | (0.0275) |
| Head's religion | Orthodox | 0.202*** | 0.109* | -0.0648 | 0.0488*** |
| | | (0.0380) | (0.0622) | (0.0666) | (0.0161) |
| | Protestant | 0.168* | -0.0296 | 0.0736 | 0.00128 |
| | | (0.0885) | (0.0669) | (0.0925) | (0.0304) |
| | Other religion | 0.0232 | -0.134* | 0.0518 | 0.00568 |
| | | (0.107) | (0.0759) | (0.146) | (0.0506) |

***Continued on next page***

***Table 2.2 (continued)***
*Probability of experiencing a shock*

| | | *Health* | *Economic* | *Natural* | *Crime/conflict/family* |
|---|---|---|---|---|---|
| Region dummy | Amhara | 0.508*** | 0.0589 | 0.295*** | 0.200*** |
| | | (0.0483) | (0.0801) | (0.0614) | (0.0435) |
| | Oromiya | 0.116** | -0.0889 | 0.0182 | 0.106*** |
| | | (0.0504) | (0.0572) | (0.0746) | (0.0374) |
| | SNNPR | 0.526*** | 0.349*** | -0.0896 | 0.123** |
| | | (0.0788) | (0.0720) | (0.0872) | (0.0480) |
| | Observations | 1630 | 1630 | 1630 | 1630 |
| | Pseudo R2 | 0.1937 | 0.0871 | 0.0679 | 0.0925 |

*Notes: The reference category for the asset quintiles is the poorest quintile; the reference category for the measure of human capital is the head of the household has no education; the reference category for religion is Muslim and for the regional dummies is Tigray.*

*Standard errors are in parentheses and allow for clustering at the Kebele level; ***,**,* refer to 1%, 5% and 10% level of significance respectively*

## 2.4.3 Shocks and coping responses: a bivariate analysis

Households rely on multiple responses to deal with the effects of shocks while at the same time a substantial proportion of households (between 13 and 37%) do not resort to an active response when faced by a shock (Table 2.3). This may be due to an inability to undertake an active response or perhaps that a shock is not particularly severe and does not require a response. For instance, in the case of health shocks the lack of a response may be due to lack of financial resources or because the condition is minor. We return to an exploration of the link between no active response and severity of shocks in the following sub-section.

With regard to internal coping responses, there is substantial variation according to the type of shock experienced. We see that households tend to rely quite heavily on their own savings to cope with natural and economic shocks (41% and 37%, respectively) while drawing on savings is less likely in the case of health and crime/conflict/family shocks (about 16% of households). Similarly, we find that households are more likely to reduce their food consumption in the case of natural and economic shocks (58% and 38% respectively) as compared to health and crime/conflict/family shocks (about 19%). A third internal household response is the sale of assets to cope with shocks. Such a response may protect households in the short-run but may have adverse long-term consequences. While this may be the case, we find that household reliance on this coping measure is relatively uniform across shocks and lies between 22 (economic shocks) to 30 per cent (health shocks). Perhaps due to thin labour markets in rural Ethiopia, increasing household labour supply in response to a shock is not very common and is exercised by about 4 to 5 per cent of households.

***Table 2.3***
*Coping responses and shocks: Descriptive statistics*

| | Per cent of households who used a specific coping response conditional on experiencing a shock | | | | | Differences in proportions (p-values) | | |
|---|---|---|---|---|---|---|---|---|
| **Coping response** | **All shocks (N=1183)** | **Health (N=509)** | **Natural (N=771)** | **Crime/conflict/family (N=113)** | **Economic (N=534)** | **Health vs. Natural** | **Health vs. Crime/conflict/family** | **Health vs. Economic** |
| Dissaved | 39 | 15.72 | 40.86 | 16.81 | 37.08 | 0.000 | 0.773 | 0.000 |
| Reduced food consumption | 50 | 19.06 | 58.24 | 18.58 | 38.20 | 0.000 | 0.908 | 0.000 |
| Sold assets (incl. food stocks) | 35 | 29.86 | 28.66 | 27.43 | 21.72 | 0.644 | 0.608 | 0.003 |
| Borrowed | 16 | 18.47 | 8.17 | 1.77 | 11.61 | 0.000 | 0.000 | 0.002 |
| Received support | 4 | 4.72 | 2.46 | 3.54 | 2.25 | 0.029 | 0.586 | 0.029 |
| Labor supply based strategy | 7 | 4.72 | 5.19 | 4.42 | 3.93 | 0.704 | 0.895 | 0.534 |
| No coping response | 30 | 21.41 | 13.36 | 30.09 | 37.08 | 0.000 | 0.047 | 0.000 |

*Notes: The last 3 columns report p-values from a test of equality of proportions.*

A key external coping response that may postpone the adverse effect of shocks is borrowing. About 18 per cent of households who face health shocks borrow in order to cope with costs of treating illnesses while this is much less common for other shock types – 12 per cent in the case of economic shocks, 8 per cent for natural shocks and 2 per cent for crime/conflict/family shocks. In terms of the source of borrowing, the bulk of the loans, across all shock types but especially in the case of health shocks, are provided by relatives and neighbours (Table 2.4). Reliance on money lenders, arguably the worst form of credit (in terms of interest rate and repayment conditions) is not very common. The qualitative interviews revealed that most households consider borrowing as a last resort (93%). Respondents provided four reasons for avoiding this coping response. First, they dislike borrowing from money lenders as the repayment period is short and the pressure involved may ruin relationships with the lender. Second, even though households tend to borrow from relatives and neighbours they have to pay interest if the loan is for longer than a short time-period, usually about a month.[15] Third, households with no livestock and land are required to provide a guarantor and this may not always be possible. Fourth, households are reluctant to borrow as it is considered a loss of face/pride and psychologically discomforting. For instance, a male respondent of Abua Kokit Kebele in Amhara Regional State mentioned,

> "… borrowing from people is like syphilis. I cannot sleep and want the earth to swallow me every moment I see the lender" [interview conducted on February 1, 2013].

Contrary to conventional wisdom (see Dekker 2004; de Weerdt and Dercon 2006; World Bank 2013), gifts, either in cash or kind from family, friends, neighbours and other informal groups is not a common response and reliance on this source ranges from a low of about 2 per cent in the case of economic shocks to 5 per cent in the case of health shocks.16 The qualitative interviews confirm the low reliance on gifts from family and friends. Not only is such support almost non-existent but almost all the households that were interviewed mentioned that they did not like to ask for help as it would hurt their pride/self-esteem and expose their inability to cope with a shock. For instance, a male respondent of Kebabi Kebele in Tigray region stated,

> "I really don't like to ask people to give me something or to help me. I prefer to sell what I have and if need be to collect and sell fire wood" [interviewed on January 21, 2013]

A female respondent from the same area said,

> "I prefer selling what I have. I have never borrowed but people may give you if you ask for it when you face such problem. If I face a strong problem of that kind, I prefer borrowing [as opposed to asking for a gift] and then repay the money by selling some stuff" [interviewed on January 21, 2013].

**Table 2.4**
*Sources of borrowing*

| | *Percent of households who borrowed from [source] given shocks* | | | | |
|---|---|---|---|---|---|
| ***Source of borrowing*** | ***All shocks (N=1183)*** | ***Health (N=509)*** | ***Natural (N=771)*** | ***Crime/conflict/family (N=113)*** | ***Economic (N=534)*** |
| Relatives | 8 | 10.41 | 4.54 | 1.77 | 3.93 |
| Neighbours | 4 | 6.29 | 1.17 | - | 2.81 |
| Money lenders | 1 | 1.18 | 0.39 | - | - |
| Formal sources | 3 | 1.18 | 2.20 | - | 5.24 |
| Iddir | 0.4 | 0.98 | - | - | - |
| Iqqub | 0.2 | - | - | - | 0.37 |

While we cannot comment on the magnitude of the reliance on different coping responses (for instance, the amount of money borrowed or value of assets sold) it is clear that households are more likely to rely on internal coping response in the face of natural and economic shocks as compared to health and crime/conflict/family shocks and on external coping responses, that is, borrowing when faced with health shocks.[17] These differences may be due to a number of factors. First, the greater reliance on internal household coping responses in the face of natural and economic shocks may be attributed to the nature of the shocks in the sense that both natural and economic shocks are relatively covariate and it may be difficult to rely on external coping responses, especially borrowing from friends and relatives, the dominant sources of credit, when a shock affects an entire community. On the other hand, health and crime/conflict/family shocks are characterized as relatively idiosyncratic and households may indeed be able to resort to external coping responses under such circumstances. Second, by their very nature, as compared to non-health shocks, coping with an episode of ill-health requires immediate access to liquid resources (cash) to finance lump-sum out-of-pocket health expenditure and hence the greater reliance on borrowing as opposed to responses such as a reduction in food consumption.[18] Consistent with this claim, the qualitative information shows that 26 of 42 interviewees borrowed to cope with health care and of these 65 per cent borrowed because they needed urgent health care either on a non-market day or at a time when they judged that the market price of the food stocks and the assets they owned was unfavourable.[19] However, shortly after, almost all of them repaid their loans by selling assets (mainly livestock but also food stocks).

### 2.4.4 Coping, shock severity and multiple shocks

The correlation between the reported severity of a shock (household was slightly, moderately or strongly affected) and the associated coping responses is shown in Table 2.5.

Across all shocks we find the proportion of households reporting no active response declines as the severity of shock increases. This is particularly pronounced in the case of health and economic shocks. In the case of health shocks the lack of an active response declines from 31 to 17 per cent when moving from slightly to strongly affected by the shock, while in the case of economic shocks the decline is from 66 to 35 per cent. These patterns support the notion that the lack of an active response, as displayed in Table 2.3, may in part be construed as evidence of a minor shock.

With regard to the four main coping responses, the proportion of households who reduce savings and consumption, sell assets or borrow is an increasing function of the perceived severity of shocks. For example, the percentage of households who borrow more than doubles for almost all shocks as we go from the least to the most severe category.

Asset sales also show the same pattern except in the case of natural shocks. With regard to health shocks, as severity increases a greater proportion of households are forced to rely on asset sales and borrowing. For example, to cope with the most severe health shocks 38 per cent of households resort to sale of assets, while this is 31 per cent in the case of crime/conflict/family shocks and somewhat lower for other shock types (27 and 24 per cent for natural and economic shocks, respectively). Differences across shocks is more pronounced in the case of borrowing with 25 per cent of households resorting to it in the case of the most severe health shock while the figures range between about 3 per cent for the most severe crime/conflict/family shock to 14 per cent for a strong economic shock.

Reliance on friends and family especially in the case of the more idiosyncratic shocks (health and crime/conflict/family shocks) is also linked to shock severity. In the case of health (crime/conflict/family) shocks only 2 (3.7) per cent of households rely on such support when faced with a minor shock while the figure is 9 (7.7) per cent in the case of a strong shock. Enhancing labour supply is not receptive to the severity of the shock as it probably depends on labour market opportunities rather than household willingness to supply labour.

### 2.4.5 Shocks and coping: multivariate analysis

A complete set of the multivariate coping response analyses is provided in Appendix Table A2.1, while estimates of the key variables of interest are displayed in Table 2.6.[20] Economic and natural shocks, that is, shocks that are relatively covariate in nature are more likely to trigger dissaving and a reduction in food consumption. For instance, households experiencing economic and natural shocks are 27 (24) and 30 (41) percentage points, respectively, more likely to dissave (reduce food consumption) as compared to households that do not experience such shocks. They also engage in asset sales (10 to 16 percentage points) but this coping response is far less likely as compared to coping by reducing savings and food consumption. Coping by relying on support from friends and family is not a viable response.

**Table 2.5**
*Coping response by reported severity of shocks (% of households)*

| Coping response | Health Slight n=202 | Health Moderate n=123 | Health Strong n=162 | Health Differences in proportions- Slight vs. Strong (p-values) | Natural Slight n=49 | Natural Moderate n=250 | Natural Strong n=470 | Natural Differences in proportions- Slight vs. Strong (p-values) |
|---|---|---|---|---|---|---|---|---|
| Disaved | 11.39 | 16.26 | 22.84 | 0.003 | 30.61 | 45.60 | 39.36 | 0.231 |
| Reduced food consumption | 8.42 | 29.27 | 27.16 | 0.000 | 42.86 | 72.00 | 52.77 | 0.187 |
| Sold assets (incl. food stocks) | 25.74 | 30.89 | 38.27 | 0.010 | 32.65 | 32.00 | 26.60 | 0.364 |
| Borrowed | 11.88 | 24.39 | 24.69 | 0.001 | 6.12 | 5.20 | 10.00 | 0.381 |
| Received support | 1.98 | 3.25 | 9.26 | 0.002 | 0.00 | 2.00 | 2.98 | 0.221 |
| Labor supply based strategy | 6.44 | 4.07 | 3.70 | 0.244 | 6.12 | 6.40 | 4.47 | 0.599 |
| No coping response | 30.69 | 15.45 | 17.28 | 0.003 | 16.33 | 9.20 | 15.11 | 0.821 |

| Coping response | Crime/Conflict/family Slight n=27 | Crime/Conflict/family Moderate n=43 | Crime/Conflict/family Strong n=39 | Crime/Conflict/family Differences in proportions- Slight vs. Strong (p-values) | Economic Slight n=61 | Economic Moderate n=150 | Economic Strong n=315 | Economic Differences in proportions- Slight vs. Strong (p-values) |
|---|---|---|---|---|---|---|---|---|
| Disaved | 14.81 | 11.63 | 25.64 | 0.290 | 26.23 | 40.67 | 36.83 | 0.113 |
| Reduced food consumption | 14.81 | 25.58 | 15.38 | 0.949 | 24.59 | 48.00 | 36.51 | 0.073 |
| Sold assets (incl. food stocks) | 14.81 | 34.88 | 30.77 | 0.137 | 9.84 | 22.00 | 24.13 | 0.013 |
| Borrowed | 0.00 | 2.33 | 2.56 | 0.402 | 6.56 | 8.67 | 13.97 | 0.112 |
| Received support | 3.70 | 0.00 | 7.69 | 0.504 | 1.64 | 0.67 | 2.86 | 0.589 |
| Labor supply based strategy | 3.70 | 2.33 | 7.69 | 0.504 | 8.20 | 6.00 | 1.90 | 0.008 |
| No coping response | 33.33 | 32.56 | 28.21 | 0.656 | 65.57 | 30.67 | 35.24 | 0.000 |

***Table 2.6***
*Probability of relying on a specific coping response*

| *VARIABLES* | *(1)* *Dissaved* | *(2)* *Reduce food consumption* | *(3)* *Sold asset* | *(4)* *Borrowed* | *(5)* *Received Support* | *(6)* *Adjusted labour supply* | *(7)* *No coping response* |
|---|---|---|---|---|---|---|---|
| Shocks | | | | | | | |
| Crime/conflict/family | 0.0861 | 0.0320 | 0.142*** | -0.0240 | 0.0117 | -0.00464 | 0.173*** |
| | (0.0596) | (0.0683) | (0.0586) | (0.0316) | (0.0161) | (0.0192) | (0.0608) |
| Health shock | 0.174*** | 0.0201 | 0.170*** | 0.152*** | 0.0336*** | 0.0137 | 0.0314 |
| | (0.0480) | (0.0481) | (0.0407) | (0.0236) | (0.0116) | (0.0128) | (0.0420) |
| Economic shock | 0.267*** | 0.241*** | 0.0979*** | 0.0678*** | 0.00403 | -0.00512 | 0.227*** |
| | (0.0408) | (0.0435) | (0.0372) | (0.0247) | (0.00599) | (0.0128) | (0.0403) |
| Natural shock | 0.301*** | 0.406*** | 0.162*** | 0.0348* | 0.00232 | -0.00218 | 0.0693** |
| | (0.0480) | (0.0453) | (0.0356) | (0.0234) | (0.00586) | (0.0127) | (0.0351) |
| Observations | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 |
| Pseudo R2 | 0.139 | 0.311 | 0.107 | 0.100 | 0.236 | 0.187 | 0.246 |

*Notes: Selected marginal effects from a probit model are reported (see Appendix Table A2.1 for the full specification); standard errors are in parentheses and allow for clustering at the kebele level; ***,**,* refer to 1%, 5% and 10% level of significance, respectively.*

Coping with health shocks, which are relatively idiosyncratic and trigger a need for cash to meet treatment costs, are met mainly by a reduction in savings, asset sales and borrowing. Comparisons across shock types reveal several clear differences. First, while households experiencing a health shock are 15 percentage points more likely to borrow as compared to those who don't, the corresponding figures for economic and natural shocks is 7 and 3 percentage points.

Given the nature of shocks (covariate) and the main source of borrowing (relatives and neighbours) it is likely that borrowing as a viable coping response is constrained when households experience natural and economic shocks. Second, a reduction in food consumption is not associated with a health shock. This is consistent with the argument that given the immediate need for cash to cover treatment costs, a reduction in food consumption is perhaps not always a viable response when households face a health shock. Based on the qualitative interviews we found that although the sale of food stocks and a reduction in food consumption are two different coping responses in the household survey, for several households selling food stocks was synonymous with a reduction in food consumption.[21] Hence, while health shocks may also tend to lead to a reduction in food consumption through sales of food stocks the effect may be postponed due to the immediate reliance on borrowing. Third, although not overwhelming there is some support from family and friends, and households that experience health shocks are 3 percentage points more likely to receive support as compared to households who do not experience such shocks. Fourth, in the case of health shocks it seems that all households experiencing such events adopt an active coping response. This is in stark contrast to the other shocks where there is evidence that a substantial proportion of households do not respond actively. In addition to the possibility that the shocks are minor and do not require a response, it is possible that in the case of covariate shocks coping responses may be limited and households may 'do nothing' as a last resort.[22]

## 2.5 Concluding remarks

Motivated by the idea that the apparent insurability of consumption for certain shocks vis-à-vis others may be driven by different coping responses to different types of shocks, this paper used data from a highly shock prone country, Ethiopia, to investigate a relatively neglected question, that is, which shocks trigger which coping responses and why. This question is important as the insurability of contemporaneous consumption against certain shocks compared to others may lead to misleading policy priorities regarding the need for various safety nets. Differences in consumption effects may in fact be caused by differences in coping responses to different shocks. This study examines these possibilities.

We found that natural shocks dominate in terms of frequency and have affected almost half of all sampled households in the past 12 months, while economic and health shocks have each affected about a third. Crime/conflict/family related shocks are rare and have been experienced only by 7 per cent of the households. In terms of scope, natural and economic shocks may be characterized as relatively covariate, or partially covariate, as their effects tend to be widespread and may affect multiple households simultaneously, as opposed to health and crime/conflict/family shocks which are relatively idiosyncratic.

Consistent with theoretical expectations, we found clear differences in terms of coping strategies across shock types. The two relatively covariate shocks – economic and natural – were more likely to trigger dissaving and a reduction in food consumption while the sale of assets and borrowing was a relatively less likely response. Coping with health shocks which typically trigger a need for cash to meet treatment costs was met by reductions in savings, asset sales and especially a far greater reliance on borrowing from informal sources as compared to other shocks. Reducing food consumption, a prominent response in the case of covariate shocks, was notable due to its absence in the case of health shocks. The lack of reliance on such an approach is consistent with the need for cash to treat health shocks which cannot be readily met by reducing food consumption. While relying on informal networks for borrowing and support is far more likely in the case of relatively idiosyncratic health shocks, a notable feature is that across all shock types, households do not tend to rely much on borrowing, support from family and friends or on enhancing their labour supply as coping approaches. Furthermore, as clearly displayed by the qualitative data, households do not like to rely on their networks for gifts and when they do borrow from family and neighbours it is a last resort, and an intermediate strategy as households attempt to repay as soon as possible by selling assets. Households were also reluctant to borrow as they have to pay interest unless a loan is for a short period, and because borrowing is associated with a loss of pride.

The links between the coping response and the shocks reported in this paper are consistent with the results in Asfaw and von Braun (2004) and Dercon et al. (2005) but suggest a different interpretation. According to Asfaw and von Braun (2004), total (purchased and own) food consumption is insured against illnesses experienced by the household head while non-food consumption is not. As they state in their paper "the hypothesis of food consumption insurance cannot be rejected in the case of total food consumption, implying that basic items that come from own production and from external sources (gifts) are better insured and insensitive to the illness of the head". An alternative interpretation of this finding, given the minor role played by gifts from family and friends, is that a reduction in food consumption is not sensitive to health shocks as such reductions are not a viable coping response to a health shock. Instead, consistent with the reduction in non-food consumption, households resort to measures such dissaving, borrowing and sales of assets in order to generate financial resources needed to deal with the health shocks. This may potentially postpone the adverse effects. Flores et al. (2008) argue along similar lines and point out that ignoring the possibility that health care may have been financed through borrowing and asset sales contributes to under estimating health shock's impoverishing effect as current consumption appears unaffected.

The analysis presented in the paper relied on cross-section data, which remains vulnerable to unobserved heterogeneity as there may be unobserved household specific traits that influence both shocks and coping strategies. While we do control for a wide range of observed characteristics and examine the sensitivity of the estimates in a number of ways, the cross-section nature of the analysis remains a limitation. Notwithstanding this shortcoming, the analysis clearly shows that informal safety nets and reliance on friends and family for support, at least in the form of gifts, even in the case of idiosyncratic shocks is virtually non-existent. While informal borrowing to deal with idiosyncratic shocks does appear to provide some succour, it is often shunned. This suggests a potentially important role for formal protection systems. Since 2005, to deal with covariate shocks, the Ethiopian government has been operating the Productive Safety Net Programme (PSNP). However, there is as yet no nationwide programme to provide financial protection against out-of-pocket expenditures needed to deal with health shocks. As shown in the paper, given the frequency of such events, and the sale of assets and the indebtedness generated by such shocks there is a need for health insurance schemes which work towards mitigating the financial consequences of health shocks.23 Whether the recently launched community based health insurance scheme can play such a role is a question that requires further scrutiny.

## Notes

[1] This paper is published in Journal of Development Studies, Vol. 50(7), (2014): pages 1009-1024. It is also available as Institute of Social Studies Working Paper No. 560 (2013) and African Studies Centre Working Paper No. 110 (2013). A Policy Brief version has appeared in the bulletin of the Organization for Social Science Research in Eastern and Southern Africa, OSSREA Bulletin XI No. 1

(February 2014) and African Studies Centre Infosheet 22 (2014). The paper is co-authored with Anagaw Mebratie, Robert Sparrow, Degnet Abebaw, Marleen Dekker, Getnet Alemu, and Arjun S. Bedi. The manuscript benefited from useful comments and suggestions of two anonymous referees.

[2] Shocks are defined as the unexpected occurrence of a certain event without regard to the magnitude of the effect. Other studies define the term as "adverse events that lead to reduction in income, consumption or loss of assets" (e.g. Dercon et al. (2005)).

[3] Typically such papers examine whether current household consumption is affected by a shock that has occurred in the past and interpret the lack of a negative effect on consumption as a sign that households are able to insure themselves against the consequences of a shock. See for example, Kochar (1999), Gertler and Gruber (2002), de Weerdt and Dercon (2006), Hoddinot (2006), Wagstaff (2007), Gertler et al. (2009), Islam and Maitra (2012) and Sparrow et al. (2014). For instance, Islam and Maitra (2012) have examined the effect of health shocks in Bangladesh, Kochar (1999) studies the effect of an agricultural shock in India, Wagstaff (2007) looks at the effect of health shocks in Vietnam and Hoddinot (2006) analyzes the effect of drought in Zimbabwe.

[4] The study is a part of a larger project designed to investigate the effect of a recently introduced pilot community based health insurance scheme. From each region four districts were selected. Three of these are districts where the pilot health insurance scheme is being offered and one is a control district.

[5] An increase in the price of goods and price of inputs was omitted as inflationary pressure has been the norm in Ethiopia for the last few years.

[6] The survey asked the following questions 1) How strongly is the household affected by these shocks? a) slightly b) somewhat c) strongly. 2) How many households were affected by this shock? a) only my household b) some households in the *Kebele* c) all households in the *Kebele* d) this *Kebele* and other *Kebeles* nearby e) affected areas beyond this *Kebele*. 3) Mention three most important coping responses used by the household. The code for the coping response employed includes: reduce savings, reduce household food consumption, sell assets, sell food stocks, borrow from -relatives, -neighbours, -money lenders, -formal sources, -*iddir* (funeral societies), -*iqqub* (credit associations), cash transfers from family/friends/neighbors, increase in labor supply, increase hired labor input, send out family member to find work outside *Kebele*, new marriage, help from informal group in kind/ labor, help from neighbors in kind/labor, other (specify) and no coping. Unfortunately we do not have information on the intensity of the coping response, that is, the extent of the reduction in consumption or the amount of borrowing.

[7] Interviews were conducted with the household head or the spouse when the head was not available.

[8] We included 12 households who had been slightly affected by a health shock and 30 households who had been moderately or strongly affected by a health shock in 2012. The initial idea was to sample about 16 households per region. However, in each of the regions after about 7 to 8 interviews it was found that there was not much variation in the responses (so called saturation) and hence the final sample was reduced and the analysis presented here is based on 42 households.

[9] The exact question in our survey is - How many households were affected by this shock? a) only my household b) some households in the *Kebele* c) all households in the *Kebele* d) this *Kebele* and other *Kebeles* nearby e) affected areas beyond this *Kebele*.

[10] A Spearman rank correlation of the quintiles of asset and consumption expenditure is 0.52. More than 34 per cent of the observations are classified in the same quintile by both measures while 27.7 per cent of observations are classified differently by more than one quintile. This is very similar to DHS report by Rutstein and Johnson (2004).

[11] Based on a three year recall period, Heltberg and Lund (2009) find that in Pakistan about two-thirds of the households have faced at least one type of shock. Based on a five year recall period, Dercon et al. (2005) find that in rural Ethiopia almost all households have suffered from at least one type of shock.

[12] Although comparisons are difficult due to differences in categorization, Dercon et al. (2005) also find a broadly similar pattern. In their paper, drought (52%) is the most common shock followed by illness (39%).

[13] Sen (1981) has documented that covariate shocks like drought lead to a collapse in demand for local services/crafts such that non-farm income activities cannot compensate for lost crop income. Based on an empirical study in West Africa, Fafchamps et al. (1998) show that non-farm income is positively correlated with covariate shocks affecting crop income.

[14] We do not control for occupation as the main occupation of the household head for 90 per cent of the households in the sample is agriculture.

[15] Respondents indicated that, if needed, they can and have borrowed from family and friends and do not need to pay any interest as long as they repay in a short time-period. In Amharic they used the term 'ye élet bidir'. The literal translation is 'a loan for days'. On further probing it seemed that as long as the loan is repaid in about less than a month then there are no interest payments.

[16] In Tanzania, de Weerdt and Dercon (2006) show a private gift is one of the coping strategies in 60 percent of the shocks, while it is considered very important in 29 per cent of shocks. Although not directly comparable as the paper combines gifts and informal loans, in Zimbabwe, Dekker (2004) reports that assistance from family and friends is the most frequently used manner of dealing with a shock. As mentioned earlier in the text we make a distinction between gifts, which do not need to be repaid and interest free loans which do need to be repaid. Our survey data show that most households borrow from friends and relatives (see Table 2.4) but loans have to be repaid and our qualitative analysis reveals that if a loan is for longer than a month interest is charged regardless of the source of the loan.

[17] Regardless of the type of shock, the qualitative interviews revealed a clear preference for internal coping responses as opposed to external coping responses.

Selling assets, mainly livestock but also crop output is the preferred coping response if a household has no savings.

[18] While some health care services (for example, ante-natal care) are available without a fee, for the most part, health care services require cash payment. It is not possible to access health care services on credit. Cash may thus be needed for transport, consultation, medication and in some cases food and lodging and informal fees.

[19] The other main reason, expressed by 27 per cent of the respondents, to resort to borrowing was lack of livestock or shortage of crop output when they need urgent health care.

[20] To examine the robustness of the estimates we (i) used a linear probability model and estimated seemingly unrelated regressions which allow error terms of the various coping response regressions to be correlated. The estimates are very similar to those reported in Table 2.6 (ii) estimated a linear probability model including kebele fixed effects. Differences between the estimates reported in Table 2.6 and specifications that included kebele fixed effects are minor and are available in Appendix Table A2.3 and A2.4.

[21] 16 of the 17 households which resorted to selling food stocks equated it with a reduction in consumption.

[22.] We also estimated specifications where the probability of using a particular coping strategy was treated as a function of the number of each shock type experienced by a household as opposed to the incidence of a shock (see Appendix Figure A2.1). There are minor differences between the two sets of estimates and the narrative emerging from both sets of estimates does not differ. These estimates are provided in Appendix Table A2.5 and A2.6.

[23] In Uganda, Dekker and Wilms (2010) have shown that health insurance protects households by reducing the amount that they borrow and by reducing asset sales when they face health shocks.

# 3 Channels of Impoverishment due to Ill-Health in Rural Ethiopia[1]

## Abstract

We use three years of household panel data and event history interviews to analyse the effects of ill-health on household economic outcomes in Ethiopia. We examine the immediate effects of a variety of ill-health measures on health expenditure and labor supply, the subsequent household coping responses, and finally the effect on household income and consumption. We find evidence of substantial economic risk in terms of increased health expenditure and reduced agricultural productivity. Households cope by resorting to borrowing and depleting assets. While households are able to maintain food consumption, we observe imperfect insurance of non-food consumption. This effect is larger for households with the lowest ability to self-insure. Maintaining current consumption through borrowing and depletion of assets is unlikely to be sustainable and displays the need for interventions that work towards reducing the financial consequences of ill-health.

## 3.1 Introduction

In recent years academic and policy debates on poverty dynamics in low-income rural settings have highlighted the impoverishing effects of illnesses due to unexpected expenditure on health care and foregone income. The bulk of the existing studies on the economic consequences of ill-health have focused on consumption (for example Cochrane 1991; Foster 1994; Townsend 1994; Asfaw and von Braun 2004; Dercon et al. 2005; Gertler et al. 2009; and Davies 2010). The mixed evidence on the ability of households to insure consumption against ill-health warrants studies that examine the channels through which ill-health affects consumption and how households cope with the effects of ill-health. Identifying the channels through which ill-health influences consumption is instructive in order to understand the longer-term effects of ill-health and to determine the scope and welfare effects of public interventions.[2]

A topical body of empirical literature has assessed the various links in this causal chain from ill-health to household consumption and potential poverty traps.[3] The contribution of this study to this growing literature lies in the richness of the data employed. First, this paper builds on Yilma et al. (2014), which is restricted to cross-section data, and offers a more comprehensive analysis of different channels through which household economic welfare is affected in rural Ethiopia. We use three years of household panel data combined with event history interviews conducted with households that have recently experienced an episode of ill-health, to analyse the effect of a variety of ill-health measures on household economic outcomes. We examine the immediate effects of ill-health on health expenditure and labor supply, the subsequent household coping responses and finally the effects of ill-health on household income and consumption. The existing literature on Ethiopia is restricted to examining the direct effect of ill-health on consumption (Asfaw and von Braun 2004; Dercon et al. 2005).

Second, in addition to examining a range of channels and economic outcomes we employ four ill-health measures of varying severity which reflect different dimensions of ill-health. The magnitude of ill-health effects on economic welfare depends on the severity and type of health measure being used. For instance, Gertler and Gruber (2002) find that minor illnesses (*change in head's illness and chronic symptoms*) are insured while less frequent and severe illnesses (*limitations in physical functioning*) are not. Other papers report similar findings.[4] The existing evidence on Ethiopia (Asfaw and von Braun 2004; Dercon et al. 2005) does not make a distinction in terms of the severity of illness and results are mixed. While Dercon et al. (2005) reject the hypothesis of full consumption insurance against the *'illness of a household member'*, Asfaw and von Braun (2004) find that food consumption is protected against the '*illness of the household head*' while non-food consumption is not insured. Distinguishing between measures of ill-health is important for a better understanding of the conduits of impoverishment as it is plausible that the nature of ill-health matters for coping responses.

To preview our results, we find strong evidence that ill-health leads to an increase in health expenditure and a reduction in crop output, and relatively weaker evidence that it leads to a drop in labor supply and total income. The effect on crop output occurs despite suggestive evidence of intra-household labor substitution, which may point to labor productivity differences and the use of productive resources for financing health care. Households cope by depleting livestock and by borrowing. While households are able to protect food consumption, we reject full consumption insurance in the case of non-food consumption particularly for households with the lowest ability to self-insure.

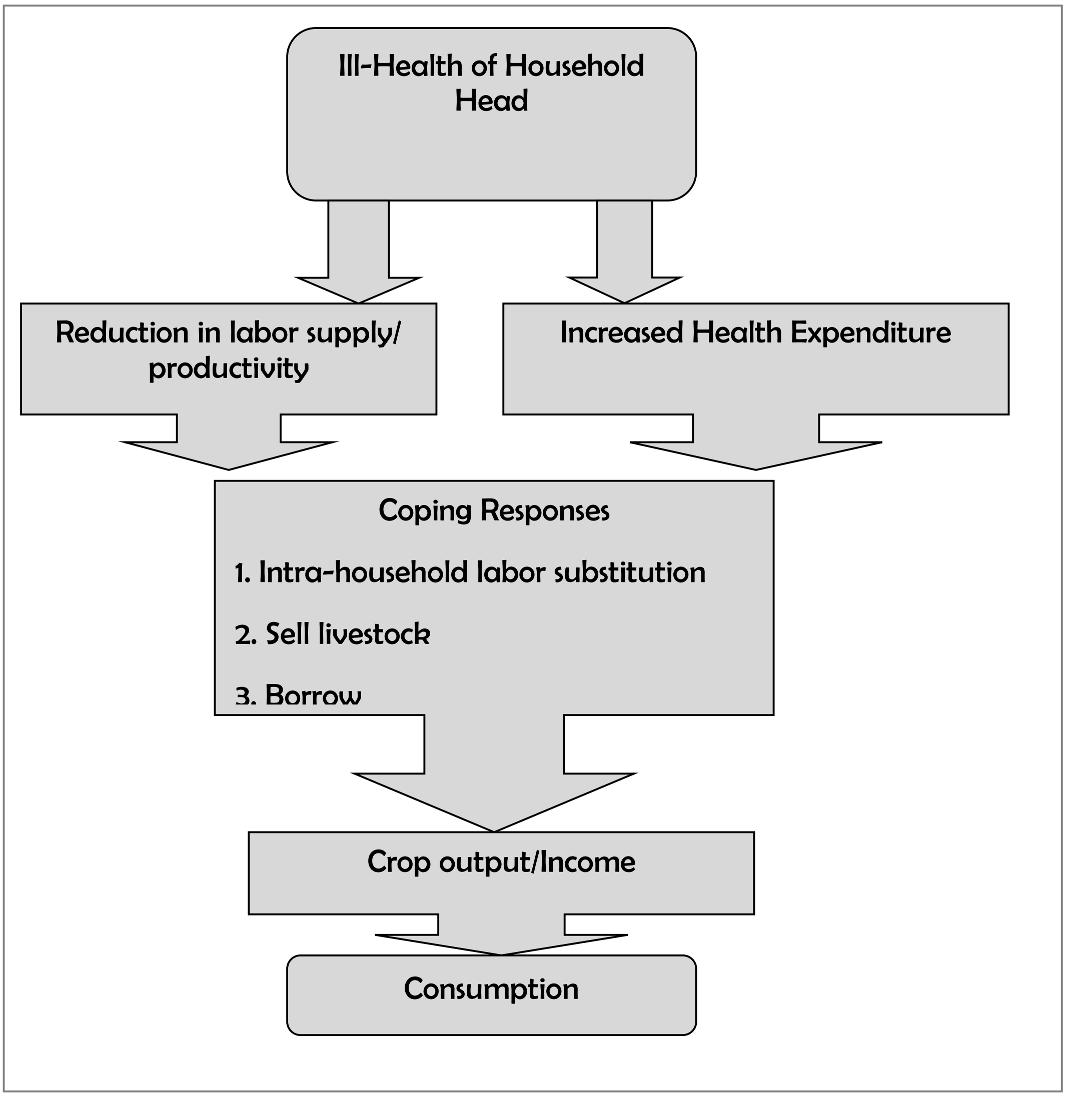
The Government of Ethiopia is currently considering a nationwide roll-out of a pilot community based health insurance (CBHI) scheme which was introduced in 13 districts in mid-2011. Our results suggest that such health insurance schemes are likely to protect households against impoverishment by reducing their exposure to health expenditure and by reducing the need to borrow and resort to the sale of assets.

The rest of the paper is organized as follows. Section 3.2 outlines a framework which guides the subsequent analysis. Section 3.3 describes data and methods. Section 3.4 presents estimates while section 3.5 contains concluding observations.

## 3.2 Analytical framework

As depicted in Figure 3.1, the two immediate effects of ill-health are its effects on labor supply and on health expenditures. Depending on its severity, ill-health may affect both labor productivity and labor supply. Whether this translates into a reduction in crop output (income) in the current context, where households are primarily engaged in self-employed agriculture, is not clear. First, as noted by Kochar (1995), it depends on whether illness occurs in the slack or peak seasons. Second, since the need for specialized skills may not be as high as compared to other occupations, there is a greater possibility for intra-household labor substitution. In addition, hiring in wage labor and/or inter-household labor substitution, for example, through local labor sharing arrangements may also help mitigate the labor supply consequences of ill-health, although hiring in labor does entail costs. Overall, the effect on income will depend on the effectiveness of a household's coping strategy, that is, whether it is possible to compensate for the entire reduction in labor supply and whether there are productivity differentials between the sick member and substituted labor.

***Figure 3.1***
*Conduits of impoverishment due to ill-health*



Conditional on seeking medical care, the second source of financial risk is increased health expenditure. The implications of this for household income and consumption depend on how health care is financed. First, households may rely on savings (including sale of food stocks) to meet such costs. To the extent that the use of savings to finance medical care curtails the ability of households to invest or purchase agricultural inputs, it may translate into reductions in crop output (income) and consumption. Second, households may sell livestock – the key household asset – and/or borrow in order to finance health care needs.[5] Such coping responses are likely to have deleterious consequences for future income and consumption, but they may allow households to protect current consumption. There are other coping possibilities, such as remittances from friends and relatives, which may have limited consequences for future income and consumption.[6] Notwithstanding this possibility, the main point is that focusing only on consumption provides an incomplete picture of the consequences of ill-health.

Following the process illustrated in Figure 3.1, we begin by examining the immediate effect of ill-health/health status of a household head on labor supply and health expenditure, followed by an assessment of the coping responses adopted by households.[7] Specifically, we consider the effects on intra-household labor substitution, livestock holdings and borrowing.[8] Finally, we provide an assessment of the effects of ill-health on income and consumption.

## 3.3 Data and Methods

### 3.3.1 Data

The study is based on three rounds of a panel household survey data collected in 16 rural districts (*Woredas*), located in four regions of Ethiopia (Tigray, Amhara, Oromiya, and SNNPR) that together account for about 86 percent of the country's population (Population Census Commission, 2008).[9] The surveys were conducted in March-April 2011, 2012 and 2013 and were purposively designed to gather information on a variety of ill-health measures of varying severity and to enable an analysis of the various channels through which these measures may influence household economic welfare. Within each district the surveys were canvassed in six randomly chosen *Kebeles* (peasant associations or villages). In each of the 96 *Kebeles*, 17 households were randomly surveyed, yielding a total of

1,632 households comprising 9,455 individuals. Of the original sample of households, 98% and 97% were re-surveyed in 2012 and 2013, respectively.

The survey contains information on a variety of individual and household socioeconomic attributes such as consumption expenditure, crop output, off-farm income, on-farm and off-farm labor supply, livestock holdings, household demographics, employment and household health conditions. The survey contains a detailed health module that asks respondents to provide for each household member age 6 and older, information on general health status (excellent, very good, good, poor, very poor), incidence of illnesses experienced in the two months preceding the survey, information on prolonged illnesses expressed as experiencing symptoms for more than 30 days, and information on the ability to carry out their activities of daily living (ADL). The ADL includes (i) stand up after sitting down, (ii) sweep the floor, (iii) walk for 5km or for an hour (if age 10 and older), (iv) carry 20 litres of water for 20 meters (if age 15 and older), and (v) hoe a field for three hours (if age 15 and older). The responses are then coded as '*can do it easily (code= 1), with a little difficulty (code=2), with a lot of difficulty (code=3)* and *not at all (code=4)*'.

In order to acquire a greater understanding of the mechanisms depicted in Figure 3.1, in January-February 2013, event history interviews were conducted with purposively selected households who had also been interviewed for the household survey. From each of the four regions, a district with a relatively high burden of ill-health was selected, and within each of the four districts, households were sampled based on the reported incidence and severity of ill-health that they had experienced. A total of 42 households were interviewed.[10]

### 3.3.2 Measures of ill-health

We use information from the health module of the survey to construct four variables which capture the health status of a household head. First, any illness experienced in the two months preceding the survey may be characterized as a short-term measure of health status, which reflects less severe illnesses and with which it might be easier to cope. Second, longer spells of illness, reflected by illness symptoms that have been persisting for 30 days or more, may have more serious labor supply consequences and require costlier medical treatment. Third, self-assessed health (SAH) status is a measure that covers multiple dimensions of health.

A key issue with the use of self-reported illness and the SAH measure is that they are likely to be affected by a household's cultural and socio-economic background (Schultz and Tansel 1997; Islam and Maitra 2012).[11] For instance, the definition of good health is likely to vary by wealth and educational status. In addition, for the same objective health condition, it is possible that the better-off or those who are more informed, report a higher incidence of illness (Sindelar and Thomas 1991). Although these are valid concerns, the panel structure of the data allows us to control for household fixed effects which should mitigate concerns about the effect of wealth and educational status on self-reported illnesses.

Perhaps a more objective health status indicator that is negatively related to income and education (Schultz and Tansel 1997; Gertler and Gruber 2002) is the ADL index, which is based on five self-rated abilities to carry out specific tasks. In contrast to self-reported illness measures, the ADL index is less likely to be endogenous to some of the outcome variables (for instance, labor supply). Our computation of this index follows Gertler and Gruber (2002) and Gertler et al. (2009) and is based on the algorithm developed by Stewart et al. (1990),

$$ADL_i = \left( \frac{Tscore_i - Minimum\,score}{Maximum\,score - Minimum\,score} \right)$$

where $Tscore_i$ is the sum of the scores on all the activities of daily living reported by individual $i$, while the minimum and maximum score relate to the minimum and maximum $Tscore$ in the data. The index takes the value one if an individual cannot perform any of the five activities (or is the least able individual in the sample) and a value of zero if the individual can perform all activities easily (or is the most able in the sample).

Descriptive statistics for the four health measures are provided in Table 3.1. In 2011, about 20% of household heads reported that they had experienced an illness in the two months preceding the survey. In 2012 and 2013 the incidence of illnesses was lower at 13.5 and 15.3%, respectively. The incidence of prolonged (and perhaps more severe) illnesses was lower and ranges between 5.4 to about 9%, depending on the year. The share of household heads reporting poor or very poor health status ranges between 6 to 9%. Consistent with the low incidence of poor health status, the ADL index ranges between 0.051 and 0.080, which indicates that, on average, household heads are readily able to carry out most of the activities of daily living. Over time, based on all four measures, there are changes in health status, although poor self-assessed health status and the incidence of prolonged illnesses are relatively stable (about 11% of household heads report a change) as compared to recent illnesses (24%) and the ADL index (30%). The fluctuation in the ADL index is similar to findings reported in Gertler and Gruber (2002) and Gertler et al. (2009).

***Table 3.1***
*Summary statistics of health measures of the household head*

| *Health measures* | *Mean / percent of household heads* | | | *Change 2011-2012 (percent of household heads)* | | | *Change 2012-2013 (percent of household heads)* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *2011* | *2012* | *2013* | *Improve* | *Same* | *Worsen* | *Improve* | *Same* | *Worsen* |
| Activities of daily living (ADL) index | 0.051<br>(0.147) | 0.058<br>(0.159) | 0.080<br>(0.187) | 10.7 | 74.1 | 15.2 | 14 | 66.1 | 19.9 |
| Prolonged illness (symptoms for more than 30 days) | 9.1 | 5.4 | 6.2 | 7.8 | 88.1 | 4.1 | 4.3 | 90.4 | 5.3 |
| Illness in the two months preceding the survey | 20.1 | 13.5 | 15.3 | 15.9 | 74.4 | 9.7 | 10.8 | 76.7 | 12.5 |
| (Very) Poor Self-Assessed Health Status | 6.1 | 6.2 | 8.9 | 4.5 | 90.9 | 4.6 | 4.9 | 87.2 | 7.8 |

*Notes: All health measures except for the ADL index are dummy variables. For ADL standard deviations are reported in parentheses. Number of observations in 2011, 2012 and 2013, depending on the health measure, range between [1627-1632], [1582-1597] and [1566-1583] respectively.*

### 3.3.3 Outcome variables

We measure household expenditure on health care by aggregating costs incurred for outpatient and inpatient care, including traditional treatments. This includes expenditure on consultation, diagnostic tests, medicine and transportation. Information on outpatient care was reported for the two months preceding the survey while information on inpatient care was provided for the twelve months preceding the survey. We extrapolate the health care costs incurred for outpatient care and use annualized health expenditure as our outcome variable of interest.[12]

The employment module of the survey records each household member's (age 6 and older) engagement in on-farm and off-farm activities in the four weeks preceding the survey.[13] The information includes the number of days worked and the average number of hours per day worked on both types of activities. The two variables that we use to capture labor supply are the total number of hours worked (both on and off-farm) in the four weeks preceding the survey by the household head and the rest of the members of the household.

***Table 3.2***
*Means and standard deviations of outcome variables*

| ***Outcome variables*** | ***2011*** | ***2012*** | ***2013*** | ***Outcome variables*** | ***2011*** | ***2012*** | ***2013*** |
|---|---|---|---|---|---|---|---|
| Total consumption | 249 | 367 | 406 | Goats # | 0.957 | 1.04 | 1.109 |
| | (162) | (692) | (529) | | (3.754) | (3.834) | (3.235) |
| Food consumption | 206 | 303 | 340 | Sheep # | 1.331 | 1.365 | 1.377 |
| | (138) | (679) | (515) | | (2.764) | (3.153) | (2.957) |
| Non-food consumption | 43 | 64 | 66 | Calves # | 0.651 | 0.687 | 0.654 |
| | (42) | (83) | (61) | | (1.019) | (1.238) | (1.944) |
| Crop output (year) | 7758 | 10781 | 11409 | Bulls # | 0.366 | 0.338 | 0.371 |
| | (14137) | (23369) | (16184) | | (1.013) | (1.085) | (1.417) |
| Total income (year) | 9354 | 12024 | 13574 | Oxen # | 1.061 | 1.031 | 1.042 |
| | (17306) | (18572) | (17222) | | (1.139) | (1.53) | (1.198) |
| Health expenditure (year) | 359 | 393 | 353 | Total labor supply (household) | 229 | 225 | 262 |
| | (1276) | (1624) | (1405) | | (247) | (213) | (215) |
| Outstanding loan | 666 | 635 | 798 | Total labor supply (head) | 92 | 89 | 102 |
| | (1450) | (1432) | (1970) | | (77) | (76) | (82) |
| | | | | Total labor supply (others) | 137 | 137 | 160 |
| | | | | | (206) | (170) | (177) |

*Notes: Unless specified the variables are in monthly terms; standard deviations are in parentheses; Number of observations in 2011, 2012 and 2013, depending on the outcome variable, range between [1539-1632], [1473-1599] and [1471-1583] respectively.*

Information on household holdings of livestock, the main household asset used to cope with the financial consequences of ill-health, is recorded for goats, sheep, calves, bulls and oxen. We use the number of different types of livestock owned rather than their monetary values. While this measure is less susceptive to reporting mistakes, it clearly does not account for differences in the quality of livestock. It is possible that using the number of different livestock may lead to an underestimate of the effect of ill-health on livestock ownership if households replace livestock that has been sold by smaller and lower quality animals. The probability of borrowing and the monetary value of all outstanding loans at the time of the survey are used to measure indebtedness.

Our measure of household income consists of two elements – the value of crop output and off-farm income. The survey gathered information on household annual output of 33 different crops. We use information on the per unit sales price of each crop to calculate the value of crop production. If a household did not sell a particular crop then we use the median district price of that crop to value crop output.[14] Off-farm income is calculated by multiplying the number of days worked in the past month by remuneration per day.[15]

Our surveys collected information on the quantity and monetary value of 41 food items consumed in the week preceding the survey and expenditure on 34 non-food items in the past month or year. This information is used to compute monthly per adult equivalent food and non-food consumption expenditures (excluding health expenditures).[16] Table 3.2 provides summary statistics of the outcome variables.

### 3.3.4 Methods

The empirical model that we use to examine the various channels outlined in Figure 3.1 is similar to the specification used in a number of studies in this genre (Gertler and Gruber 2002, Asfaw and von Braun 2004, Genoni 2012) and is written as,

$$\Delta(Y_{ivt}) = \alpha_0 + \alpha_1 T_t + \theta_v + \beta \Delta H_{ivt} + \sum_j \lambda_j \Delta X_{ivt} + \Delta\varepsilon_{ivt} \quad (3.1)$$

For household $i$ located in village $v$, we model changes in an outcome variable of interest ($\Delta Y_{ivt}$) as a function of a time dummy (T), a village fixed effect ($\theta_v$), changes in the health conditions of the household head ($\Delta H_{ivt}$), and changes in a vector of controls ($\Delta X_{ivt}$) which includes household economic status (main occupation of the household head, asset index quintiles, membership in a productive safety net programme), demographics (age, sex and religion of the head, log household size[17] and the age-sex composition of the household), human capital (educational status of the head), social capital (if the household has someone to rely on in times of difficulties), the incidence of shocks in the twelve months preceding the survey (economic, natural and crime-conflict related) and a random error term ($\Delta \varepsilon_{ivt}$).[18] Our focus is on the coefficient, $\beta$, which reflects the sensitivity to ill-health.[19] We estimate several variants of (3.1) using different empirical methods, depending on the nature of the dependent variable, and provide robust standard errors clustered at the village level.

The use of a difference specification allows us to identify the effect of ill-health on various outcomes after controlling for the effects of time-invariant observed and unobserved variables. For instance, a household's unobserved health endowment is likely to be correlated with the ill-health measures and labor supply and might confound estimates of the effect of illness on labor supply. However, as long as such endowments are time-invariant, estimates based on (3.1) will not be affected.[20] The set of village fixed-effects controls for village-specific differences in, among others, susceptibility to covariate shocks. To control for time-varying household specific shocks we estimate (3.1) with the inclusion of a set of variables that captures the incidence of natural, economic and crime/conflict related shocks.

Despite relying on a difference specification and the inclusion of various controls, there are additional empirical issues that warrant a discussion. For a number of the outcome variables, such as health expenditure or the value of outstanding loans, the distributions are censored at zero and skewed. One possibility is to work with logged values of the variables and we do so in the case of consumption where we log consumption before differencing. For the other outcome variables, due to zero values we work with levels. However, since the outcome variables are in first differences, skewness is minimized even without a log transformation.[21] Thus, similar to Gertler and Gruber (2002), the tables reported in the main body of the paper are based on using OLS or logit models with changes in log consumption and changes in levels of other outcomes as dependent variables.

Nevertheless, as a robustness check and to probe the sensitivity of our results to the choice of specification, we also use several alternative models that are commonly applied to deal with such non-normal distributions. Following Genoni (2012), who argues that a quartic root is a good approximation to the log transformation for positive values, we also estimated (3.1) using changes in the quartic root of the outcome variables (Appendix Table A3.2). With regard to health expenditure, Buntin and Zaslavsky (2004) note that zero observations can be accommodated without difficulty by employing one part generalized linear models. To this end, we also estimated the effect of ill-health on health expenditure using a Poisson fixed effects model (Appendix Table A3.3).[22] Finally, we estimated equation (3.1) by adding 1 to the variables with zero outcomes and then taking logs and differencing the variables (Appendix Table A3.4).

Changes in the health measures used in (3.1) and a number of the outcome variables may be simultaneously determined. For instance, household-specific changes in income due to crime or conflict may also have adverse effects on health outcomes. Several remarks are in order. First, we explicitly control for the incidence of natural, economic and conflict/crime related shocks in (3.1). Second, we use several measures of ill-health and while the self-reported illness measures are more likely to be susceptible to feedback effects it is less likely that the ADL index is as prone to such feedback effects. For instance, concerted labor effort is more likely to translate into illness as compared to influencing the ability of individual to engage in various activities of daily living.

The effect of ill-health on consumption estimated with equation (3.1) may also be misleading if ill-health alters preferences. Conventional tests of consumption insurance assume that preferences are stable. However, if changes to health status induce changes in consumption preferences then this may confound the estimates of $\beta$ in equation (3.1). In our empirical work we control for changes in demographic variables that may lead to a preference shift. Furthermore, we examine the effect of ill-health affecting a household head on household consumption. Considering that the average household size in our baseline data is almost six, it seems unlikely that the health of the head will drive changes in household consumption preferences. To assess potential preference shifts we use a test suggested by Gertler and Gruber (2002). We examine how estimates of (3.1) vary by the ability of a household to self-insure.[23] If the effect of ill-health on consumption is due to changes in the budget constraint, then full consumption insurance will be less likely to hold as the ability to self-insure reduces. On the other hand if health induced preferences play a dominant role then the effect of ill-health on consumption should not be correlated with the ability to self-insure. Our measure of self-insurance ability is household ownership of livestock (sheep, goats, calves and bulls) in the first round of the survey. As discussed earlier, selling livestock, especially smaller ruminants, is often used to finance health care and in the current context serves as our measure of the ability of a household to self-insure.[24]

A final concern is that the introduction of the community based health insurance scheme during the time period covered by the data may potentially confound estimates based on (3.1). While an evaluation of the scheme is beyond the scope of this paper and the variable is excluded from our baseline specification we do examine the sensitivity of our estimates to household uptake of the scheme (Appendix Table A3.1, A3.5 and A3.6).

## 3.4 Estimates

### 3.4.1 Effects on health expenditure and labor supply

Estimates of the effect of the four health measures on annual health expenditure are reported in column 1 of Table 3.3. All the measures show that experiencing an illness or deterioration in health status leads to a statistically significant increase in health expenditure. For instance, households experiencing an illness in the two months preceding the survey are likely to experience an 874 Birr increase in annual household health expenditure while those who experience prolonged illness may expect to spend about 1,100 Birr on health care. These figures amount to between 4.1 and 5.3% of annual household consumption in 2012.[25] A change in the household head's health status to poor/very poor is associated with an expenditure increase of about 793 Birr a year while a deterioration in the ADL index of 0.2, which is equivalent to a movement from being able to easily do all the activities included in the index to an inability to execute one of them, is associated with additional expenditures of about 334 Birr a year.[26] Although the magnitudes of the estimates are not directly comparable, the statistical significance and signs of the estimates are robust to quartic root and log transformations (Appendix Table A3.2 and A3.4), and estimation by Poisson fixed effects, Generalised Linear Models and Two Part Models (Appendix Table A3.3).

**Table 3.3**
*Effect on health expenditure, labor supply and income*

| | Health expenditure | Labor supply (head) | Labor supply (others) | Labor supply (household) | Crop output | Total income |
|---|---|---|---|---|---|---|
| ADL index | 1,670*** | -17.06* | 36.94 | 25.31 | -3,180 | -3,527 |
| | (542.8) | (9.463) | (30.16) | (35.56) | (2,048) | (2,476) |
| Prolonged illness | 1,108*** | 1.355 | 20.82 | 21.22 | -1,247* | -802.3 |
| | (301.5) | (4.767) | (12.91) | (14.17) | (637.2) | (1,933) |
| Illness | 873.9*** | -0.260 | 16.50** | 15.52 | -2,008** | -564.6 |
| | (168.1) | (3.307) | (7.889) | (9.724) | (914.5) | (850.5) |
| (Very) poor SAH | 792.7*** | -12.23*** | 10.54 | -4.556 | -1,234* | -1,577 |
| | (254.0) | (4.648) | (14.78) | (17.27) | (687.5) | (1,006) |

*Notes: Each coefficient is from a separate linear regression of equation (3.1). Number of observations ranges between [2664-3106]. Not reported but included in the specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

Column 2 of Table 3.3 provides estimates of the effect of the various health measures on the labor supply of the household head while columns 3 and 4 contain labor supply estimates for other household members and the household as a whole, respectively. Deteriorations in self-assessed health status and in the ADL index are associated with reductions in labor supply of between 12 and 17 hours per month (13 to 19% of average household head labor supply in 2012). The two other illness measures do not translate into statistically discernible effects on the labor supply of the household head, at least in our baseline specification. It is of course possible that the household head continues to supply the same amount of labor but is not as productive, an issue we are not able to test directly. Our robustness check for quartic root transformation (Appendix Table A3.2) shows statistical significance for three out of four ill-health measures while the log transformation shows statistical significance for all of the ill-health measures (Appendix Table A3.4). Given the more conservative baseline estimates, we conclude that there is weak evidence of negative labor supply effects.

### 3.4.2 Coping Responses

We do not find strong evidence that a decline in the labor supply of the household head is matched by an increase in the labor supply of other members of the household. Although all coefficients are positive, it is precisely estimated only in the case of recent illnesses. The overall outcome of this process of adjustment is that at the level of the household an illness episode or deterioration in health status does not translate into a reduction in labor supply.[27] Our robustness checks for quartic root and log transformations show statistically significant over-compensation for illnesses, which might be due to productivity differences. The event-history interviews also provide evidence of intra-household labor substitution which support the suggestive statistical evidence. For instance,

> "I mostly feel sick partly due to old age but my children are healthy. In this month, I went to a private clinic in Woreta [nearest town] due to a worm in my foot... It took about 15 days till I completed the medication and I was not working but my children did the work well. All of them are grown-ups and I have educated them. [Male respondent, Woji Arbamba Kebele of Amhara region, Interview conducted on 31st January 2013]"

While households might be able to (over-) compensate for health-induced reductions in the labor supply of the household head, due to differences in productivity or the need to raise resources to finance required health care there may still be negative consequences.[28] In addition to loss of income such consequences include loss of leisure time, and if households draw on child work then it may come at the cost of school attendance. The event-history interviews show that the choice can be difficult especially if households need to rely on school-going children,

> "My husband had something in his leg over a weekend… In total he was sick for over two weeks and did not do anything. He wanted our son to

> miss school and work on the field but my son refused as it was exam time. I supported him because his attendance at school for the whole year would mean nothing if he doesn't sit for an exam. We then left the farm unattended. There was some crop output eaten by livestock during that time. The animals belonged to our relatives and we couldn't sue them. [Female respondent, Woji Arbamba Kebele of Amhara region, Interview conducted on 1st February 2013]"

We are not able to identify, at least statistically, the effects of ill-health on the use of wage labor as a coping response (due to data unavailability). However, the event history interviews reveal that households do use this option. As mentioned by one of the respondents,

> "Recently I had typhoid… Because we may lose output/ income when we fall ill, I employed labor for 500 birr to transport my harvest. I wouldn't have spent this much if I was not ill. There is no one to do the work at home as my husband is in a seasonal migration and my children are too young. [Female respondent, Kebabi Kebele of Tigray region, Interview conducted on 22 January 2013]"

Other coping responses include borrowing and the sale of assets. Estimates of equation (3.1) for the probability of borrowing and the amount of the loan are provided in columns 1 and 2 of Table 3.4, while the remaining columns pertain to the effects of ill-health on household livestock holdings. All measures of ill-health lead to an increase in the probability of having an outstanding loan. Depending on the health measure, the probability of borrowing is 1.7 to 2.6 times higher if a household head has experienced a negative health change, while 3 of the 4 health measures are associated with increases in the amount of the loan. For a household head experiencing deterioration in physical functioning equal to the average observed for the sub-sample that saw a fall in the ADL index (0.22 points), loan amounts may be expected to increase by 93 Birr. Illnesses and unfavourable changes in SAH are associated with increases in borrowing of 277 and 289 Birr, respectively. Prolonged illness is also associated with an increase in the loan amount but the coefficient is not statistically significant.[29] To place this effect in perspective, consider that the increases in borrowing associated with changes in the three health measures (which are statistically significant) amount to between 25 and 36% of the increase in health expenditure induced by these measures.[30] Our robustness checks confirm this conclusion (Appendix Table A3.2 and A3.4).

Consistent with the comments distilled from the event history interviews we find that households tend to sell smaller ruminants in response to ill-health. As shown in Table 3.4, a worsening of the SAH status of the household head and a decline in the ADL index are both associated with declines in household holdings of sheep.[31] The estimates imply that for every 10 households that experience a decline in SAH status, almost 4 sell a sheep to finance health care needs. In the case of the ADL index, for every 10 household heads who experience the average deterioration observed in the sample about 1 will sell livestock (sheep). There is no effect on household holdings of bulls and calves while change in ADL has some negative effect on ox holdings. As discussed earlier, focusing only on the number of animals may not provide a complete picture as smaller and lower quality sheep/goats may have replaced household livestock holdings.

**Table 3.4**
*Effect on indebtedness and asset stock*

| | *Any loan* | *Loan amount* | *Goat* | *Sheep* | *Bulls* | *Calves* | *Oxen* |
|---|---|---|---|---|---|---|---|
| ADL index | 2.575** | 422.3** | -0.198 | -0.620** | -0.0659 | -0.172 | -0.164* |
| | (1.170) | (187.7) | (0.377) | (0.285) | (0.0856) | (0.109) | (0.0891) |
| Prolonged illness | 1.666** | 106.0 | -0.152 | -0.181 | 0.000700 | 0.0278 | -0.0506 |
| | (0.345) | (92.81) | (0.137) | (0.141) | (0.0463) | (0.0622) | (0.0351) |
| Illness | 2.028*** | 277.1*** | -0.0552 | -0.0568 | 0.0203 | -0.0139 | -0.0314 |
| | (0.295) | (86.29) | (0.0984) | (0.110) | (0.0468) | (0.0441) | (0.0289) |
| Poor/very poor SAH | 1.820*** | 288.9** | -0.127 | -0.364** | -0.0128 | -0.0401 | -0.0201 |
| | (0.383) | (133.4) | (0.130) | (0.167) | (0.0492) | (0.0646) | (0.0394) |

*Notes: Each coefficient is from a separate regression of equation (3.1). The column labelled, "Any loan", contains odds ratios from a logit fixed-effects model. Number of observations for this column ranges between [1892-1926]. The rest of the coefficients are from linear regression estimates of (3.1). Number of observations for these ranges between [3063-3110]. Not reported but included in the specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

### 3.4.3 Effect on income and consumption

The analysis so far shows that the increase in health expenditure and the decline in the labor supply of the head of the household due to ill-health are somewhat compensated through increases in intra-household labor substitution, borrowing and sales of small ruminants. Yilma et al. (2014) show that financial support from family and friends is very limited and in addition to sales of assets and borrowing, households rely on savings to meet their health care needs. As long as this saving is earmarked for productive purposes, it might compromise productivity.

Estimates reported in Table 3.3, columns 5 and 6 display a negative association between ill-health and crop output and between ill-health and total income. The estimates for crop output are statistically significant and large while those for total income are also large but not statistically significantly different from zero. However, these imprecise effects for total income should perhaps not be interpreted as evidence of households' ability to compensate for losses in crop output by resorting to off-farm income-generating activities, especially given the fact that the point estimates for two of the four ill-health measures suggest a larger decline in total income than crop output. In fact, the robustness checks for the quartic root and log transformations (Appendix Tables A3.2 and A3.4) show statistically significant negative coefficients in three of the four ill-health measures for total income.

The observed decline in crop output despite finding no evidence of reduced total household labor supply could suggest that intra-household labor substitution involves a cost in terms of reduced labor productivity. Alternatively, the event history interviews tend to suggest that crop output is affected by the diversion of household savings to finance health care needs as opposed to being used to buy agricultural inputs. For instance, consider,

> "My wife is sick of modern illness, TB. She is recurrently sick and goes to health facilities quite often. I spent around 5000 birr. Her illness has affected our harvest. Because of health expenditure, I couldn't buy inputs of production (high yield seeds and fertilizer) on time and hence, reduced my output. [Male respondent, Oumbulo Tenkaka Kebele of SNNPR, Interview conducted on 11th February 2013]"

> "My daughter had a stomach complaint for more than a week. I took her to a traditional healer but she couldn't get better. Then, I took her to a

health center... I spent 300 birr for that. Due to her illness, I didn't work on my vegetable garden. As I used the money I put aside for seeds, I ran out of cash to buy the seeds to plant my vegetables. Although, after sometime, I worked off-farm (dig-out sand and sell) and planted vegetables, I do not expect as much output as I planted it late. [Male respondent, Jara Damuwa Kebele of SNNPR, Interview conducted on 15th of February 2013]"

Finally, we examine the effect of ill-health on consumption, both for the full sample and for sub-groups based on self-insuring ability (own buffer stock/livestock or not). Focusing on the full sample, the estimates reported in Table 3.5 show that, regardless of the ill-health measure, there is no effect on total consumption. In fact, in the case of the ADL index there is a positive although statistically insignificant effect while for the other measures the coefficients are essentially zero.[32] Food consumption also displays a similar pattern except in the case of ADL where it is significantly positive. The estimates for non-food consumption are clearly more sensitive to ill-health and in the case of prolonged illnesses the estimates indicate an 8% reduction in non-food consumption. For other measures non-food consumption remains unaffected. The finding that non-food consumption is more sensitive to ill-health than food consumption is similar to results for Ethiopia reported in Asfaw and von Braun (2004) and Sparrow et al. (2014) for Indonesia.

Conditioning on households' ability to self-insure we find that across all health measures, those with a lower ability to self-insure experience a negative although statistically insignificant effect on total consumption and food consumption. It is only in the case of non-food consumption that such households experience large negative effects. Prolonged illness and deterioration in SAH are associated with a reduction of 15% and 26%. Consumption for those with a greater ability to self-insure remains unaffected except in the case of ADL where we find a positive effect. The latter could happen if better-off households should (and are able to) consume more in order to recover faster. Furthermore, for the better off, a desire for a quicker recovery might also induce more expensive non-food expenditure that relate to costs of care. This heterogeneity supports the argument that the effects of ill-health on consumption are driven by tighter budget constraints as opposed to preference shifts.

**Table 3.5**
*Consumption insurance*

| | | Total | Food | Non-food |
|---|---|---|---|---|
| ADL index | Full sample | 0.116 | 0.158* | 0.167 |
| | | (0.0789) | (0.0816) | (0.117) |
| | Poor | -0.132 | -0.0862 | -0.165 |
| | | (0.138) | (0.153) | (0.208) |
| | Non-poor | 0.222** | 0.278*** | 0.280** |
| | | (0.0958) | (0.0916) | (0.136) |
| Prolonged illness | Full sample | 0.00522 | 0.0203 | -0.0835* |
| | | (0.0292) | (0.0327) | (0.0454) |
| | Poor | -0.0807 | -0.0747 | -0.150* |
| | | (0.0516) | (0.0653) | (0.0888) |
| | Non-poor | 0.0424 | 0.0603 | -0.0530 |
| | | (0.0430) | (0.0447) | (0.0649) |
| Illness | Full sample | 0.000158 | 0.00873 | -0.0328 |
| | | (0.0287) | (0.0295) | (0.0352) |
| | Poor | -0.0551 | -0.0392 | -0.0510 |
| | | (0.0627) | (0.0618) | (0.0765) |
| | Non-poor | 0.0114 | 0.0190 | -0.0326 |
| | | (0.0306) | (0.0319) | (0.0394) |
| (Very) poor SAH | Full sample | 0.0119 | 0.0262 | -0.00925 |
| | | (0.0382) | (0.0389) | (0.0512) |
| | Poor | -0.121 | -0.0922 | -0.265*** |
| | | (0.0793) | (0.0836) | (0.0929) |
| | Non-poor | 0.0590 | 0.0709 | 0.0775 |
| | | (0.0432) | (0.0440) | (0.0554) |

*Notes: Each coefficient is from a separate linear regression of equation (3.1). Number of observations for the full sample, 'poor' sample and 'non-poor' sample range between [2936-3077], [747-783] and [2189-2294] respectively. Not reported but included in our specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. All dependent variables are log-transformed. Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

Additionally, the different patterns suggest that it is ill-health induced reductions in income and labor supply that influence consumption and not the reverse. The effect heterogeneity results presented here are similar to those found in Indonesia by Gertler and Gruber (2002), Gertler et al. (2009) and Sparrow et al. (2014).

## 3.5 Concluding remarks

This paper used three waves of panel data and event history interviews conducted in rural Ethiopia to examine i) the channels of impoverishment due to ill-health ii) the coping responses adopted by households, and iii) the effects on current household economic welfare (income and consumption).

We find that there is substantial economic cost due to forgone crop output and increased health expenditure. Although the labor supply of the household head declines due to ill-health, there is some evidence of intra-household labor substitution which limits the overall reduction in household labor supply. However, possibly due to productivity differences between the head's labor and the substituted labor and diversion of productive resources for health care, there is a decline in crop output. We also find that ill-health is associated with asset depletion, increases in the probability of indebtedness and increases in the amount of outstanding loans. We did not find evidence to reject the null hypothesis of food consumption insurance against ill-health. However, non-food consumption declines for certain measures of ill-health. This effect is magnified for households with the lowest ability to self-insure.

The results presented in this paper support the recent move of the Government of Ethiopia to expand and scale-up a pilot community based health insurance scheme. Given the effects of ill-health on asset depletion and household indebtedness, both of which are likely to exert negative effects on consumption in the long-run, such a scheme may provide protection against future vulnerability.

## Notes

[1] An earlier version of this paper is available as Institute of Social Studies Working Paper No. 592 (2014). The manuscript benefited from useful comments and suggestions from conference participants at the Annual Bank Conference on Africa, Paris, France (June 2014) and at the Nordic Conference on Development Economics, Helsinki, Finland (June 2014). The paper is co-authored with Anagaw Mebratie, Robert Sparrow, Marleen Dekker, Getnet Alemu, and Arjun S. Bedi.

[2] See Chetty and Looney (2006) for an argument that social safety nets are valuable even if consumption is not sensitive to ill-health.

[3] For instance, Mohanan (2013) considered the effects of accidents on debt and consumption; Sparrow et al. (2014) and Bales (2013) consider the effects of ill-health on health expenditure, self-reported coping responses, income and consumption; Genoni (2012) traces the effects on assets, transfers, income and consumption; Islam and Maitra (2012) on assets, loans and consumption; Nguyet and Mangyo (2010) examine both labor supply and consumption; Wagstaff and Lindelow (2010) focus on health expenditure and consumption; Wagstaff (2007) on health expenditure, income and consumption; Lindelow and Wagstaff (2005) on labor supply, health expenditure and income; Gertler and Gruber (2002) on labor supply, health expenditure, income and consumption and Kochar (1995) on loans and income.

[4] For instance, based on data from the United States, Cochrane (1991) analyzed the effect of '*short and long spells of illness (work days lost)*' on consumption growth and found that the former is insured while the latter is not. In an early study on India, Townsend (1994) reported that the '*percentage of year that an adult male is sick*' has no effect on household consumption. More recently, using data from Bangladesh, Islam and Maitra (2012) also find that household consumption is fairly well insured against '*incidence of illness, number of days of sickness and death of the main income earner*'. In contrast, Gertler et al. (2009) in Indonesia and Wagstaff (2007) in Vietnam report that consumption is sensitive to '*limitations in physical functioning*', and '*death of a working member, incidence of long spells of hospitalization and sizable drop in BMI of the head*', respectively.

[5] In his work on Ethiopia, Dercon (2004) notes that livestock is the most important marketable asset and accounts for more than 90% of the value of assets. The event-history interviews that we conducted revealed that selling livestock,

especially smaller ruminants (sheep and goats) rather than larger animals is a common coping response.

[6] While relying on family and friends for support is a potential coping strategy, in a related paper (Yilma et al. 2014) we find that only 5% of households who have experienced a health shock in the year preceding the survey relied on such support.

[7] We focus on the health status of the household head as it is likely that this individual is the main bread winner. Asfaw and von Braun's (2004) paper on Ethiopia also focuses on the health status of the household head. Other papers such as Gertler and Gruber (2002), Lindelow and Wagstaff (2005) and Nguyet and Mangyo (2010) also focus on the health status of the household head.

[8] In principle we should also examine the effect of ill-health on household savings and gifts from family and friends. Unfortunately, we do not have data on savings.

[9] The study is part of a larger project designed to investigate the effects of pilot community based health insurance (CBHI) scheme which was launched in mid-2011. Twelve of the districts included in the survey host the CBHI scheme while one district in each region serves as a control.

[10] Interviews were conducted with the household head or the spouse when the head was not available. We included 12 households which had been slightly affected by a health shock and 30 households which had been moderately or strongly affected by a health shock in 2012. The initial idea was to sample about 16 households per region. However, in each of the regions after about seven to eight interviews it was found that there was not much variation in the responses (so called saturation), and hence the final sample was reduced.

[11] For formal sector employees there are concerns that individuals may report that they are ill in order to justify reduced labor supply (reporting bias for the sake of sick leave). This is unlikely in the current case of, mainly, a sample of self-employed workers.

[12] The three surveys were conducted at the same time each year. This reduces concerns regarding seasonal variations in health conditions. Estimates based on computing the health expenditure variable on the basis of adding outpatient spending in the last two months to inpatient spending in the last 12 months, instead of extrapolating, lead to similar results. However, as may be expected the coefficients decline.

[13] About 75% of households work exclusively on-farm.

[14] If information on sales price was not available for particular crop in a particular *woreda* we worked with the median sales price for that crop in the zone.

[15] Information on off-farm income is restricted to those who work as employees and excludes income from off-farm self-employment. Income earned from such activities was not gathered. This is likely to lead to an underestimate of total income for 93 households who (at baseline) reported that a household member was engaged in off-farm self-employment activities.

[16] We use the adult equivalent measures suggested by Dercon and Krishnan (1998). The average family size is about 4.8 adults.

[17] In the consumption regressions, we do not control for household size since the dependent variables are in per adult equivalent terms.

[18] The asset index is constructed on the basis of a principal components analysis of 68 items including housing conditions, land size, consumer durables, farm equipment and livestock. For specifications where livestock is a dependent variable we exclude the asset index. The productive safety net program is a social protection program intended for food insecure households.

[19] Specifically in the case of consumption, theory predicts that either through self-insurance mechanisms (such as savings) or inter-household risk sharing arrangements (support from friends and relatives) or borrowing and selling assets, households will aim to insulate consumption from transitory shocks to household income. That is, the coefficient on the measure of ill-health should not be statistically different from zero. Although households may adopt various coping measures, each of which might be difficult to observe, the test of full insurance measures the overall contribution of all coping responses.

[20] Additionally, to the extent that the ill-health measures, and for that matter other variables, are measured with error, differencing the data will eliminate time-invariant measurement error.

[21] Typically, for almost all the outcome variable, first differences are evenly distributed over negative and positive values around a zero mean.

[22] While we are more interested in health expenditure and not just the probability of incurring health expenditure we also estimated two part models considering a) probit for the probability of spending b) expected log health expenditure given spending using OLS c) expected health expenditure using a generalized linear model with log link and gamma distribution. Regardless of the model, as is discussed later in the text, we find that all four measures of ill-health are associated with increases in the probability of spending and the amount spent on health care.

[23] While the idea behind the test is the same, the manner in which we operationalize the ability to self-insure is different from that used by Gertler and Gruber (2002).

[24] The event-history interviews revealed households tend to selling sheep and goats rather than larger animals. Of the 1599 households in the second round, 26% did not have any of these animals (buffer stock livestock) while the rest have at least one.

[25] In 2012, on average, annual household consumption was Birr 21,139 ($1,213).

[26] The mean change in the ADL index among those whose physical functioning declines is 0.22.

[27] In the case of three of the four illness measures, the increase in labor supply provided by other household members is larger than the reductions in labor supply.

[28] In Indonesia, Genoni (2012) also finds suggestive evidence for intra-household labor substitution.

[29] In the case of quartic root and log transformations all measures of ill-health increase loan amounts.

[30] These percentages are based on estimates reported in Tables 3.3 and 3.4. In the case of SAH status, ill-health increases borrowing by 289 Birr and health expenditure by 793 Birr. For illness the corresponding figures are 277 and 874 and in the case of ADL they are 93 and 367 (at the average change in ADL).

[31] We also estimated this effect using 'Tropical Livestock Unit' as a dependent variable. Results are statistically significantly negative only for ADL (results are not reported but could be available upon request).

[32] Gertler and Gruber (2002) and Gertler et al. (2009) reject the hypothesis of full consumption insurance against limitations in physical functioning. Using data from Indonesia, Genoni (2012) finds that neither consumption nor assets are responsive to limitations in physical functioning. In the current case, although there is no effect on consumption, we do find an increase in indebtedness and depletion of assets induced by limitations in physical functioning.

# 4 Impact of Ethiopia's Community Based Health Insurance on Household Economic Welfare[1]


## Abstract

In 2011, the Government of Ethiopia launched a pilot Community-Based Health Insurance (CBHI) scheme. This paper uses three rounds of household survey data, collected before and after the introduction of the CBHI pilot, to assess the impact of the scheme on household consumption, income, indebtedness and livestock holdings. We find that enrolment leads to a 5 percentage point – or 13 percent – decline in the probability of borrowing and is associated with an increase in household income. There is no evidence that enrolling in the scheme affects consumption or livestock holdings. Our results show that the scheme reduces reliance on potentially harmful coping responses such as borrowing. This paper adds to the relatively small body of work which rigorously evaluates the impact of CBHI schemes on economic welfare.


## 4.1 Introduction

Various forms of health insurance have been advocated as market based risk-transfer mechanisms with the potential to guard against the impoverishing effects of ill-health (see Gertler and Gruber 2002, Xu et al. 2003, Asfaw and Von Braun 2004, Leive and Xu 2008). The recent proliferation of Community Based Health Insurance (CBHI) schemes in many developing countries emanates partly from a need to provide financial protection against unexpected health care costs and to enhance access to modern health care. As a prelude to national coverage, in June 2011, the Ethiopian Government introduced a pilot CBHI scheme in thirteen Woredas (districts) across the four main regional states that constitute 86 percent of the population (Population Census Commission, 2008).[2] The aim of this paper is to examine the impact of this scheme on measures of household economic welfare: consumption, income, indebtedness and livestock.

The economic burden associated with the incidence of ill-health has been documented in a recent but rapidly growing literature on poverty dynamics. Most of these studies examine the consumption implications of health shocks while some delve into the portfolio of coping responses adopted by households.[3] A number of studies show that households in the informal rural sector rely on traditional coping responses such as selling assets and informal borrowing to deal with the adverse consequences of ill-health (Heltberg and Lund 2009, Dekker and Wilms 2010, Sparrow et al. 2014, Yilma et al. 2014). These coping responses are not cost free but entail a compromise – protecting current consumption at the cost of future vulnerability (Flores et al. 2008).

Health insurance primarily addresses out-of-pocket health expenditure, one of two sources of household financial stress from ill health. The second source is forgone income due to declining capacity to work. While health insurance schemes are not designed to curb this source of vulnerability, they might still provide some protection to households' agricultural income by facilitating early recovery and by reducing pressure on households to reallocate resources meant for productive purposes (for instance, to buy fertilizers and high value seeds) to medical spending. By reducing reliance on potentially harmful coping responses, such as borrowing at usurious rates, health insurance schemes might protect household's economic welfare both in the short and the long-run.

Although analyses of the impact of health insurance has been the subject of a large body of empirical literature, much of this work has focused on health care utilization and out-of-pocket (OOP) health expenditure or on induced behavioural responses such as moral hazard (Leon 2012). Reviews of the literature by Ekman (2004) and Mebratie et al. (2013a) conclude that the evidence base is questionable with regard to the financial protection provided by CBHI. The bulk of the CBHI evaluation literature, with few exceptions[4], relies on cross-section based association and does not identify causal effects. Ignoring self-selection in voluntary insurance uptake is likely to lead to biased estimates of the impact of CBHI.

Moreover, while there are studies that examine whether health insurance helps protect income or wealth from declining due to ill-health (Levy 2002, Lindelow and Wagstaff 2005) or have studied the effect of such schemes on consumption (Wagstaff and Pradhan 2005), there are relatively few studies that have evaluated the impact of such schemes on indebtedness and livestock.

This paper uses three rounds of household panel data – a baseline and two follow-up surveys. The presence of a baseline survey enables us to examine self-selection and to control for both observable and unobservable time invariant factors which may affect self-selection. To identify the effect of the scheme on income, consumption, livestock and indebtedness we rely on both fixed effects and matching methods and compare results for different control groups (within and across pilot and non-pilot districts).

We find that enrolment in the CBHI scheme decreases the probability of indebtedness by 13 percent. We also find a negative, yet imprecise, effect on the amount of outstanding loans. There is no statistically significant impact on livestock holding and consumption. However, crop output and total income increase by 9 to 10 percent of baseline values.

The remainder of the paper is organized as follows. Section 4.2 provides the context and design of the CBHI scheme. Section 4.3 describes the data. This is followed by a brief discussion on the how the scheme may be expected to influence outcomes. Section 4.5 describes the empirical approach and section 4.6 presents the results. Finally, section 4.7 concludes.

## 4.2 CBHI scheme design

In June 2011, as part of the new health sector financing reform (HSFR) initiatives, the Ethiopian Government launched a pilot CBHI scheme in 13 districts in the four main regions (Tigray, Amhara, Oromiya, and SNNPR) of the country.[5, 6] Regional administrative bodies selected these districts based on directives provided by the Federal Ministry of Health (FMoH). The selection criteria require that the districts fulfil five conditions while in practice selection was based on two conditions: undertaking HSFRs and geographical accessibility of health centers (located close to the main road).[7]

The community element to the CBHI scheme is that villages (Kebeles) decide whether or not to join (based on a simple majority vote), and are subsequently involved in management and supervision. Possibly due to prior sensitization activities, all villages in pilot districts voted in favour of the scheme. Once a Kebele agrees to join, household enrolment is voluntary. To reduce adverse selection, enrolment is at the household level rather than the individual (FMoH 2008).

***Table 4.1***
*Premium and CBHI uptake per region*

| *Region* | *Premium per month (ETB)* | | *CBHI uptake (%)* | |
|---|---|---|---|---|
| | *For all core HH members* | *Per each non-core HH member* | *April 2012* | *April 2013* |
| Tigray | 11 | 2.5 | 33.9 | 50.2 |
| Oromiya | 15 | 3 | 44.2 | 44.5 |
| SNNPR | 10.5 | 2.1 | 35.3 | 35.4 |
| Amhara | 3 per any member | | 49.5 | 62.7 |
| Total | | | 40.7 | 48.2 |

*Notes: A one-time registration fee of ETB 5.00 apply for all households; Payment interval: Tigray (annual), Amhara (biannual), Oromiya (annual or biannual), SNNPR (three times a year or quarterly). Core household members include parents and their children below the age of 18.*

Benefit packages, registration fees, premiums and premium payment methods are similar within regions but vary slightly across regions (Table 4.1).[8] While in Amhara region the unit of contribution is the individual (ETB 3 per individual per month) in other regions it is the household. For core household members (parents and minor children), household level monthly premiums range between ETB 10.50 in SNNPR to ETB 15 in Oromiya (Table 4.1). For each additional non-core household member the monthly premium lies between ETB 2.10 and ETB 3.00. On average, the combined premiums for core household members (parents and underage children) amount to about 1-1.4 percent of household monthly non-medical expenditure.[9] The CBHI scheme is subsidized by both the central and regional/district governments. The central government provides a general subsidy amounting to a quarter of the premium collected at district level while the regional and district level governments cover the costs of providing a fee waiver for the poorest 10 percent of the population.[10]

The benefit package includes both outpatient and inpatient service utilization at public facilities. Enrolled households may not seek care in private facilities unless a particular service or drug is unavailable at a public facility. The scheme excludes treatment abroad and treatments with large cosmetic value such as artificial teeth and plastic surgery. The referral procedure requires members to visit health centers before they may be referred to hospitals (district or regional). Those who do not follow this referral procedure need to cover half the costs of their medical treatment.[11] In our sample, CBHI uptake reached 41 percent in April 2012 and 48 percent in 2013 (see Table 4.1). This is comparable to the official overall figure reported by Abt Associates (45.5 percent in December 2012). Although there is not much of a difference between uptake in April 2012 (41 percent) and uptake in April 2013 (48 percent), the speed of uptake is remarkable compared to experiences in other African countries. Uptake in Senegal after two years was 4.8 percent (Smith and Sulzbach, 2008), in Tanzania 2.8 percent after six years (Chee et al., 2002), in Mali 11.4 percent after six years (Diop et al., 2006), and in Rwanda 35 percent after seven years and 85 percent after nine years (Shimeles, 2010).

## 4.3 Data

We use three-rounds of a household panel data set, collected in March/April of 2011, 2012 and 2013. The first round was collected a few months before the launch of the CBHI scheme and serves as a baseline. Sixteen districts located across four main regions of the country (Amhara, Oromiya, Tigray and SNNPR) are included in the survey. For each region we include all three districts that implemented the CBHI pilot and one selected non-pilot district. The non-pilot districts were chosen based on the same criteria that were used to select the pilot districts. Within the districts we applied a two stage sampling design, randomly sampling villages (six from each district) and the households (17 from each village). The total sample size in the first round is 1,632 households comprising 9,455 individuals, of which 98 and 97 percent were successfully re-surveyed in 2012 and 2013.

The survey instrument contains information on a variety of individual and household socio-economic attributes such as consumption expenditure, crop output, off-farm income, assets, outstanding loans, household demographics, employment and health conditions. The total value of all outstanding loans at the time of the survey is used to measure indebtedness. We record the number of various livestock types owned rather than their monetary values. It is important to acknowledge that although this is less prone to reporting error, we are not able to capture livestock quality and size differences. Our measures of income are value of crop output and total income in the past 12 months. The survey asks if a household produced any of 33 crop items listed and how much is produced. We calculate the value of crop production using the per unit sales price of each item. If the household did not sell that item we rely on the median price of that item in the district or zone. Crop output is the sum of the monetary value of all items produced in the past year. Total income is the sum of crop output and off-farm income. Off-farm income is calculated by multiplying the number of days worked in the past month with the average cash equivalent remuneration per day. Monthly off-farm income is multiplied by 12 to get annualized figures. This is then aggregated at the household level before adding it to crop output. Our measure of consumption is monthly non-medical per adult equivalent consumption.[12] The survey collected the quantity and monetary value of 41 food items consumed in the last week and consumption expenditure on 34 non-food items in the past month or year, depending on the item. Both food and non-food consumption expenditures are then converted to their monthly equivalents, in per adult equivalent terms.

In addition to the surveys, we also conducted event history interviews with 42 purposively selected households across the four regions. We make occasional references to this qualitative information.

## 4.4 CBHI and expected effects

In principle, since enrollment in CBHI enables access to free care, it might reduce the necessity to rely on coping responses that are less preferred by households. For example, Yilma et al. (2014) find that borrowing is a last resort used by households primarily to meet urgent health care needs.[13] Hence, we expect access to CBHI to reduce the probability of borrowing/indebtedness. Distress sales of livestock to finance urgent health care needs are also expected to decline. Hence, we expect an increase in livestock ownership.[14] The possibility that insurance protects households against the income effects of health shocks has been noted in China (Lindelow and Wagstaff 2005). There are two ways in which CBHI might affect household income. First, it might reduce the negative impact on labor supply by facilitating early treatment and fast recovery. Second, as the following quotes suggest, credit constrained rural households tend to finance health care using cash that has been saved for buying fertilizers or seeds. Subsequent delays in production or loss of productivity might compromise household income.

> "My wife is sick of modern illness, TB. She is recurrently sick and goes to health facilities quite often. I spent around 5000 birr. Her illness has affected our harvest. Because of health expenditure, I couldn't buy inputs of production (high yield seeds and fertilizer) on time and hence, reduced my output. [Male respondent, Oumbulo Tenkaka Kebele of SNNPR, Interview conducted on 11th February 2013]"

> "My daughter had a stomach complaint for more than a week. I took her to a traditional healer but she couldn't get better. Then, I took her to a health center... I spent 300 birr for that. Due to her illness, I didn't work on my vegetable garden. As I used the money I put aside for seeds, I ran out of cash to buy the seeds to plant my vegetables. Although, after sometime, I worked off-farm (dig-out sand and sell) and planted vegetables, I do not expect as much output as I planted it late. [Male respondent, Jara Damuwa Kebele of SNNPR, Interview conducted on 15th of February 2013]"

## 4.5 Methods

The non-random nature of insurance uptake is an important empirical concern in identifying the causal effect of CBHI. Demand for health insurance may be driven by affordability or latent health status, in which case simple differences in outcomes between CBHI enrolled and non-enrolled households may not be viewed as causal effects of the scheme. Tables 4.2 and 4.3 suggest non-random uptake. At baseline, households that subsequently take up CBHI have higher crop output and income, are more likely to have borrowed, have larger outstanding loans, and larger livestock holdings than households that do not insure.

**Table 4.2**
*Baseline differences in outcome variables: insured vs non-insured*

| | Insured households | Non-insured households | | |
|---|---|---|---|---|
| | | All districts | Pilot districts | Control districts |
| | (N=656) | (N=911) | (N=527) | (N=384) |
| **Income** | | | | |
| Crop output | 8499.0 | 5985.0*** | 6551.3*** | 5212.8*** |
| | (9104.3) | (7044.6) | (7440.0) | (6395.8) |
| Total income | 10017.2 | 7091.8*** | 7757.6*** | 6196.2*** |
| | (9828.0) | (7335.5) | (8089.1) | (6075.1) |
| **Consumption** | | | | |
| Total | 244.7 | 249.4 | 241.9 | 259.6 |
| | (146.9) | (170.4) | (162.5) | (180.5) |
| Food | 201.1 | 206.3 | 200.6 | 214.0 |
| | (125.4) | (144.6) | (144.8) | (144.3) |
| Non-food | 43.8 | 43.0 | 41.2 | 45.5 |
| | (39.6) | (45.1) | (37.7) | (53.6) |
| **Indebtedness** | | | | |
| Outstanding loan (%) | 37.5 | 26.0*** | 26.6*** | 25.3*** |
| | (48.4) | (43.9) | (44.2) | (43.5) |
| Total outstanding loan | 880.3 | 527.6*** | 492.8*** | 575.4*** |
| | (1689.2) | (1259.3) | (1172.7) | (1369.5) |
| **Livestock** | | | | |
| Goats # | 1.2 | 0.8** | 0.7** | 0.8 |
| | (5.3) | (2.2) | (2.2) | (2.1) |
| Sheep # | 1.8 | 1.0*** | 0.9*** | 1.2*** |
| | (3.0) | (2.6) | (2.2) | (3.0) |
| Bulls # | 0.4 | 0.3** | 0.3* | 0.3** |
| | (1.4) | (0.7) | (0.6) | (0.7) |
| Calves # | 0.8 | 0.6*** | 0.6*** | 0.5*** |
| | (1.2) | (0.9) | (0.9) | (0.8) |
| Oxen # | 1.4 | 0.8*** | 0.9*** | 0.8*** |
| | (1.3) | (1.0) | (1.0) | (0.9) |

*Notes: Columns 1-4 report mean (standard deviation; Statistical significance refers to differences in means between the control group and the insured households: *** 0.01, ** 0.05, * 0.1. Crop output refers to total value of production in the past one year. Total income is the sum of crop output and off-farm income. All livestock types refer to number of livestock owned. All monetary values are in Ethiopian Birr (ETB)*

***Table 4.3***
*Baseline differences in covariates: insured vs non-insured*

| | (1) Insured households (N=656) | | (2) All non-insured households (N=911) | | (3) Non-insured in pilot districts (N=527) | | (4) Non-insured in control districts (N=384) | | (5) P-value | (6) P-value | (7) P-value |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | St.dev | Mean | St. dev | Mean | St. dev | Mean | St. dev | Ho: (1=2) | Ho: (1=3) | Ho: (1=4) |
| **Health measures** | | | | | | | | | | | |
| Head ADL Index | 0.044 | (0.136) | 0.054 | (0.151) | 0.063 | (0.167) | 0.042 | (0.124) | 0.181 | 0.033 | 0.792 |
| Any illness (%) | 46.8 | (49.9) | 46.9 | (49.9) | 51.2 | (50.0) | 40.9 | (49.2) | 0.977 | 0.130 | 0.064 |
| Any chronic illness (%) | 16.3 | (37.0) | 17.1 | (37.7) | 20.3 | (40.3) | 12.8 | (33.4) | 0.671 | 0.076 | 0.122 |
| Any paralysis (%) | 4.9 | (21.6) | 3.4 | (18.1) | 4.4 | (20.4) | 2.1 | (14.3) | 0.143 | 0.677 | 0.024 |
| Any poor/very poor SAH (%) | 15.9 | (36.6) | 11.9 | (32.3) | 15.4 | (36.1) | 7.0 | (25.6) | 0.022 | 0.820 | 0.000 |
| **Covariates** | | | | | | | | | | | |
| Head does not work (%) | 1.2 | (11.0) | 1.9 | (13.5) | 1.7 | (13.0) | 2.1 | (14.3) | 0.314 | 0.484 | 0.275 |
| Head farmer (%) | 93.6 | (24.5) | 87.5 | (33.1) | 91.3 | (28.3) | 82.3 | (38.2) | 0.000 | 0.130 | 0.000 |
| Head domestic worker (%) | 2.6 | (15.9) | 5.7 | (23.2) | 3.6 | (18.7) | 8.6 | (28.1) | 0.003 | 0.313 | 0.000 |
| Head other employment (%) | 2.6 | (15.9) | 4.9 | (21.7) | 3.4 | (18.2) | 7.0 | (25.6) | 0.019 | 0.406 | 0.001 |
| PSNP member (%) | 25.8 | (43.8) | 20.9 | (40.7) | 10.3 | (30.5) | 35.2 | (47.8) | 0.022 | 0.000 | 0.001 |
| Asset quintile 1 (%) | 10.5 | (30.7) | 24.9 | (43.3) | 23.3 | (42.3) | 27.1 | (44.5) | 0.000 | 0.000 | 0.000 |
| Asset quintile 2 (%) | 15.5 | (36.3) | 23.3 | (42.3) | 22.2 | (41.6) | 24.7 | (43.2) | 0.000 | 0.003 | 0.000 |
| Asset quintile 3 (%) | 19.4 | (39.5) | 21.2 | (40.9) | 21.1 | (40.8) | 21.4 | (41.0) | 0.377 | 0.468 | 0.439 |
| Asset quintile 4 (%) | 23.9 | (42.7) | 17.8 | (38.3) | 18.2 | (38.6) | 17.2 | (37.8) | 0.003 | 0.017 | 0.011 |
| Asset quintile 5 (%) | 30.6 | (46.1) | 12.8 | (33.5) | 15.2 | (35.9) | 9.6 | (29.5) | 0.000 | 0.000 | 0.000 |
| Social capital (%)a | 40.5 | (49.1) | 35.6 | (47.9) | 34.4 | (47.6) | 37.2 | (48.4) | 0.051 | 0.033 | 0.306 |
| Head is male (%) | 88.1 | (32.4) | 85.6 | (35.1) | 86.1 | (34.6) | 84.9 | (35.9) | 0.153 | 0.315 | 0.138 |
| Head age | 47.3 | (13.1) | 45.6 | (14.5) | 46.4 | (14.7) | 44.5 | (14.2) | 0.022 | 0.319 | 0.001 |
| Head has no education (%) | 43.1 | (49.6) | 48.5 | (50.0) | 48.8 | (50.0) | 48.2 | (50.0) | 0.032 | 0.050 | 0.109 |
| Head education informal (%) | 15.9 | (36.6) | 11.2 | (31.5) | 10.2 | (30.4) | 12.5 | (33.1) | 0.007 | 0.005 | 0.137 |
| Head education primary (%) | 36.9 | (48.3) | 35.8 | (48.0) | 35.9 | (48.0) | 35.7 | (48.0) | 0.637 | 0.701 | 0.682 |

*Continued on next page*

***Table 4.3 (continued)***

*Baseline differences in covariates: insured vs non-insured*

| | (1) Insured households (N=656) | | (2) All non-insured households (N=911) | | (3) Non-insured in pilot districts (N=527) | | (4) Non-insured in control districts (N=384) | | (5) P-value Ho: (1=2) | (6) P-value Ho: (1=3) | (7) P-value Ho: (1=4) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | St.dev | Mean | St. dev | Mean | St. dev | Mean | St. dev | | | |
| Head education secondary or more (%) | 4.1 | (19.9) | 4.5 | (20.7) | 5.1 | (22.1) | 3.6 | (18.8) | 0.717 | 0.413 | 0.704 |
| Head Muslim (%) | 18.8 | (39.1) | 32.5 | (46.9) | 17.1 | (37.7) | 53.6 | (49.9) | 0.000 | 0.457 | 0.000 |
| Head Orthodox (%) | 64.6 | (47.8) | 41.9 | (49.4) | 54.1 | (49.9) | 25.3 | (43.5) | 0.000 | 0.000 | 0.000 |
| Head Protestant (%) | 15.7 | (36.4) | 22.2 | (41.6) | 25.6 | (43.7) | 17.4 | (38.0) | 0.001 | 0.000 | 0.463 |
| Head other Christian/religion (%) | 0.9 | (9.5) | 3.4 | (18.1) | 3.2 | (17.7) | 3.6 | (18.8) | 0.001 | 0.004 | 0.002 |
| Log HH size | 1.7 | (0.4) | 1.6 | (0.4) | 1.7 | (0.5) | 1.6 | (0.4) | 0.000 | 0.004 | 0.001 |
| Male (age<=5) share % | 6.5 | (10.4) | 7.9 | (12.1) | 7.5 | (11.8) | 8.5 | (12.6) | 0.017 | 0.124 | 0.007 |
| Female (age<=5) share % | 6.5 | (10.4) | 8.1 | (12.4) | 7.4 | (11.4) | 8.9 | (13.6) | 0.010 | 0.165 | 0.001 |
| Male [6 18] share (%) | 21.7 | (17.1) | 19.0 | (17.1) | 19.0 | (16.8) | 19.0 | (17.6) | 0.002 | 0.007 | 0.014 |
| Female [6 18] share (%) | 19.2 | (15.9) | 18.5 | (16.3) | 18.7 | (16.1) | 18.3 | (16.7) | 0.437 | 0.604 | 0.410 |
| Male [19 45] share (%) | 15.3 | (13.0) | 16.0 | (13.6) | 16.1 | (13.8) | 15.8 | (13.3) | 0.336 | 0.320 | 0.558 |
| Female [19 45] share (%) | 16.3 | (11.7) | 16.1 | (11.4) | 16.2 | (12.0) | 16.0 | (10.6) | 0.724 | 0.846 | 0.671 |
| Male [46 60] share (%) | 4.6 | (8.3) | 3.8 | (7.6) | 3.6 | (7.2) | 4.1 | (8.0) | 0.045 | 0.026 | 0.328 |
| Female [46 60] share (%) | 5.3 | (11.6) | 4.8 | (12.1) | 5.0 | (11.9) | 4.6 | (12.3) | 0.420 | 0.640 | 0.345 |
| Male [60+] share (%) | 3.3 | (9.4) | 3.0 | (9.3) | 3.5 | (10.2) | 2.3 | (8.0) | 0.579 | 0.673 | 0.092 |
| Female [60+] share (%) | 1.2 | (7.2) | 2.8 | (11.4) | 3.0 | (12.2) | 2.5 | (10.3) | 0.002 | 0.002 | 0.022 |
| Health shock (%) | 32.1 | (46.7) | 31.2 | (46.3) | 37.0 | (48.3) | 23.2 | (42.3) | 0.710 | 0.075 | 0.002 |
| Crime/conflict shock (%) | 5.6 | (23.1) | 7.7 | (26.6) | 8.9 | (28.5) | 6.0 | (23.8) | 0.116 | 0.030 | 0.820 |
| Economic shock (%) | 37.7 | (48.5) | 30.3 | (46.0) | 36.2 | (48.1) | 22.1 | (41.6) | 0.002 | 0.604 | 0.000 |
| Natural shock (%) | 45.5 | (49.8) | 49.0 | (50.0) | 49.3 | (50.0) | 48.4 | (50.0) | 0.176 | 0.189 | 0.359 |

*Notes: Columns 1-4 report mean and standard deviation. P-values for tests of differences in means are reported in columns 5-7; [a] social capital takes the value of 1 if the household has someone to rely on at times of difficulties.*

However, we see little differences in consumption. A naive comparison of post intervention outcomes would overestimate the impact of CBHI on income and livestock and underestimate the impact on indebtedness.

We therefore estimate a household fixed effects model that controls for both observed and unobserved time-invariant confounding factors.

$$Y_{it} = \beta CBHI_{it} + \delta T_t + \varphi X_{it} + \theta_i + \varepsilon_{it} \qquad (4.1)$$

where $Y_{it}$ is the outcome of interest for household $i$ at time $t$, the dummy variable $CBHI_{it}$ indicates whether household $i$ is insured in year $t$, and $T$ reflects year dummy variables for each of the three years. Household fixed effects are captured by $\theta_i$ and $\varepsilon_{it}$ is a random error term. Time varying controls $X_{it}$ include demographics, various measures of socio-economic status, shocks and household head characteristics (see Table 4.3 for a list of covariates). We estimate the above equation with and without $X_{it}$. If the confounding role of time-variant unobserved characteristics is minimal, then we would expect similar treatment effects across these two specifications.[15] In addition, we also combine the fixed effects approach with propensity score matching (PSM). CBHI uptake is modelled as a function of baseline characteristics, and we estimate equation (4.1) only for households on common support.

We have two groups of control households: uninsured households in pilot districts and households from non-pilot districts. Each control group introduces different sources of bias. For the pilot districts, the voluntary nature of the scheme could induce selection bias. The fixed effects would purge selection effects if these are based on time-invariant characteristics. Pilot districts are also prone to spill-over effects. However, these are most likely to be relevant to health care use and not for economic outcomes, at least not in the short term.[16]

The control districts are drawn from the same regions and fulfil the criteria stipulated by the government in selecting CBHI districts, while any remaining geographical differences will be controlled for by the fixed effects. Although, fixed effects cannot deal with aggregate shocks we explicitly control for information on 22 different shock types (natural shock, crime/conflict related shock, health shock and economic shock). Our robustness check for excluding covariates also tests if the results are sensitive to excluding these shocks.

Finally, there remains a possible confounding effect from other social programs that share targeting and selection criteria with the CBHI pilot. We are aware of only one such social safety net program in rural Ethiopia, the PSNP (Productive Safety Net Program). For both sets of control households, we estimate models with and without an indicator variable for PSNP.

***Table 4.4***
*Welfare effects of CBHI*

| | *FE with covariates* | | | *FE with covariates after matching* | | |
|---|---|---|---|---|---|---|
| | *All districts* | *control districts* | *Pilot districts* | *All districts* | *control districts* | *Pilot districts* |
| **Income** | | | | | | |
| Crop output | 459.9 | 286.6 | 816.4* | 418.6 | 243.8 | 785.4* |
| | (477.4) | (572.4) | (460.7) | (481.8) | (573.8) | (470.1) |
| Total income | 675.7 | 427.8 | 1,092* | 593.9 | 338.2 | 1,027* |
| | (571.3) | (632.7) | (593.6) | (577.3) | (633.7) | (604.2) |
| **Consumption** | | | | | | |
| Total | 18.01 | 25.03 | 12.38 | -6.556 | -1.874 | -14.96 |
| | (27.45) | (30.75) | (33.02) | (21.34) | (24.82) | (26.35) |
| Food | 18.59 | 26.94 | 10.87 | -5.655 | 0.405 | -16.18 |
| | (26.70) | (29.95) | (32.25) | (20.67) | (23.92) | (25.68) |
| Non-food | 0.113 | -1.044 | 2.436 | 0.0201 | -1.285 | 2.467 |
| | (2.969) | (3.581) | (3.166) | (3.047) | (3.748) | (3.228) |
| **Indebtedness** | | | | | | |
| Loan (0/1) | -0.0506** | -0.0540** | -0.0340 | -0.0483** | -0.0484** | -0.0341 |
| | (0.0222) | (0.0237) | (0.0238) | (0.0225) | (0.0235) | (0.0243) |
| Loan amount | -44.87 | -51.24 | -16.72 | -36.24 | -38.18 | -10.62 |
| | (69.76) | (77.20) | (70.32) | (70.81) | (77.93) | (71.84) |

*Continued on next page*

***Table 4.4 (continued)***
*Welfare effects of CBHI*

| | *FE with covariates* | | | *FE with covariates after matching* | | |
|---|---|---|---|---|---|---|
| | *All districts* | *control districts* | *Pilot dis-tricts* | *All districts* | *control districts* | *Pilot dis-tricts* |
| **Livestock** | | | | | | |
| Goats # | -0.0835 | -0.0357 | -0.129 | -0.0836 | -0.0247 | -0.136 |
| | (0.141) | (0.124) | (0.151) | (0.145) | (0.127) | (0.156) |
| Sheep # | -0.0321 | 0.0237 | -0.0808 | -0.0336 | 0.0205 | -0.0808 |
| | (0.113) | (0.129) | (0.114) | (0.114) | (0.130) | (0.115) |
| Bull # | 0.0453 | 0.0421 | 0.0247 | 0.0458 | 0.0447 | 0.0209 |
| | (0.0362) | (0.0415) | (0.0349) | (0.0368) | (0.0425) | (0.0356) |
| Calves # | -0.0177 | -0.0360 | -0.00440 | -0.0210 | -0.0380 | -0.00400 |
| | (0.0631) | (0.0547) | (0.0647) | (0.0644) | (0.0562) | (0.0664) |
| Oxen # | 0.0451 | 0.0590 | 0.0286 | 0.0439 | 0.0574 | 0.0277 |
| | (0.0452) | (0.0480) | (0.0467) | (0.0464) | (0.0495) | (0.0483) |

*Notes: The column headings refer to the choice of control group: all districts (all non-insured households included), control districts (only non-insured households in control districts included), and pilot districts (only non-insured households in pilot districts included). Standard errors (in parentheses) are clustered at the village level. Results are broadly similar when excluding the time-varying covariates. A list of covariates is given in table 4.3. In the case of livestock we exclude the asset index quintiles as the index includes number of livestock. Range of number of observations: first column (4230-4665), second column (2816-3101), third column (3153-3520), fourth column (4059-4483), fifth column (2722-3003), sixth column (3053-3412). 66 out of 1548 observations are outside the common support region [0.086-0.869].*

*Statistical significance: *** 0.01, ** 0.05, * 0.1*

***Figure 4.1***
*(Selected) outcome variables by insurance status across years*


## 4.6 Estimates

Table 4.4 presents treatment effects using different control groups. Across methods we find statistically significant positive impact on income (crop output and total income) for the pilot district comparison only. While the magnitudes of the estimates decline as we exclude households that are off support, we find that crop output and total income increase by ETB 785 and ETB 1027, respectively or 9 to 10 percent of baseline values. While the coefficients are also positive when we use households in non-pilot districts as controls, the estimates are not precise. The results provide no evidence that CBHI affects household consumption, as the coefficients lack statistical significance and the magnitudes are small.

We find a negative impact on the probability of having outstanding loans ranging between 4 to 5 percent, depending on methods and control groups, which translates to about 13 percent of baseline values.[17] Figure 4.1 shows that the source of this effect is a decline in the proportion of indebted insured households. There are also negative coefficients for the amount of outstanding loans although these are imprecise. Estimates for all types of livestock are not statistically significant.

## 4.7 Conclusion

This paper explored the impact of Ethiopia's CBHI pilot scheme on household economic welfare. We used three rounds of a household panel dataset, which included one baseline and two follow-up surveys. We deployed different specifications of a household fixed effects model and compared results across different control groups (within and across pilot and non-pilot districts).

We found that enrolment in CBHI decreases the probability of indebtedness by about 5 percentage points. Compared to the proportion of households who were indebted at baseline (37.5 percent), this effect corresponds to a 13 percent decline. We found no statistically significant impacts on consumption and livestock holdings while there is some evidence that CBHI is associated with increases in annual crop output and total income of about 9 to 10 percent.

Thus, the main benefit of the scheme is its effect on reducing the need to borrow and rely on savings. This may have longer-term benefits in reducing vulnerability to other forms of shocks. A related study has found a sharp impact on increasing health care utilization (Mebratie et al. 2013b). The combined results provide support to the government's recent move to extend the CBHI pilot to a total of 161 districts for further testing. However, a nationwide scale up requires an examination of the scheme's financial sustainability.

## Notes

[1] A shorter version of this paper is published in the *World Bank Economic Review (*forthcoming*).* It is also available as Institute of Social Studies Working Paper No. 590 (2014). The manuscript benefited from useful comments and suggestions from conference participants at the Annual Bank Conference on Development Economics (ABCDE), Washington DC, USA (June 2014). The paper is co-authored with Anagaw Mebratie, Robert Sparrow, Marleen Dekker, Getnet Alemu, and Arjun S. Bedi.

[2] This came following a successful low-cost health service extension program designed to increase the supply of preventive and basic curative health services. See its impact evaluation in Admassie et al. (2009).

[3] See, amongst others, Gertler and Gruber 2002, Wagstaff 2007, Wagstaff and Lindelow 2010, Islam and Maitra 2010, Genoni 2012, Sparrow et al. 2013, Mohanan 2013.

[4] Jowett et al. (2003) for Vietnam, Levine et al. (2014) for Cambodia and Lu et al. (2012) for Rwanda, find statistically significant negative effects of CBHI on OOP health spending. Wagstaff et al. (2009) find no statistically significant effects for China.

[5] Although initially the plan was to launch the pilot scheme in 3 districts in each of the four regions, an additional district in Oromiya region volunteered to join the pilot scheme and was included.

[6] The main components of the health sector financing reform include revenue retention and utilization by health facilities, fee waiver and exemption of certain services, and establishment of private wings in public hospitals.

[7] The complete set of selection criteria include (1) Willingness of district authorities to implement the scheme (2) Commitment of districts to support the scheme, (3) Geographical accessibility of health centers (4) Quality of health centers, (5) The implementation of cost recovery, local revenue retention, and public pharmacy policies in health centers.

[8] The design of the scheme is based on a feasibility study conducted by an international consultancy company, Abt Associates, which is also responsible for implementation and monitoring of the scheme in collaboration with relevant government bodies at the federal and local level.

[9] In 2011, monthly household non-medical expenditure was ETB 1103 (USD 1 equals ETB 18).

[10] These households are categorized as indigent groups (households without land, house, or any valuable assets). In December 2012 about 9 percent of total eligible households had received a fee waiver.

[11] Access to tertiary level care differs across regions. While in Oromiya coverage includes hospitals located outside the region, in SNNPR they may visit only the nearest public hospital. In Amhara and Tigray, CBHI enrollees may visit any public hospital within the region but not outside the region.

[12] We adopt the age-sex based adult equivalent household size suggested by Dercon and Krishnan (1998).

[13] Yilma et al. (2014) also show that selling assets and relying on savings are prominent responses to health shocks in these villages.

[14] However, if livestock is used as a saving mechanism and is used to pay for premiums, the effect of CBHI may not be clear.

[15] Results without covariates are reported in the Appendix, Table A4.1.

[16] We run a placebo test where treatment indicator takes a value of 1 if uninsured household lives in pilot district and 0 otherwise. We do not find any indication of spill-over effects. Results are reported in the Appendix, Table A4.2.

[17] The estimates for the pilot-district control group are, however, imprecise.

# 5 Households' Expectations of Medical Expenditures and Insurance in Rural Ethiopia[1]


## Abstract

The perceived risk of medical expenses is presumed to be the major determinant of health insurance enrolment. Yet little is known about the formation of such risk perceptions, including the extent to which they are based on past spending. Also lacking is evidence on the ability of households to predict their medical expenses. This paper reports on a unique elicitation of subjective probabilities of medical expenditures from rural Ethiopians who are offered the opportunity to purchase health insurance. We assess the validity of their responses and find patterns which indicate that the data do contain information. We find that expectations are positively related to past expenses and that the correlation with past medical spending exceeds the serial correlation in realized expenditures, suggesting that respondents overestimate persistence and, on average, underestimate the potential gains from insurance (since a large proportion of households spend nothing in a given year). Expected expenditure is weakly but significantly positively correlated with the spending that actually materialises. Despite being able to anticipate expenses, to some extent, there is little or no evidence that expectations influence the decision to take out health insurance, although plans to insure are positively related to the perceived dispersion of medical expenses.


## 5.1 Introduction

Reduction in exposure to medical expenditure risk underpins the case for social health insurance and is presumed to motivate enrolment in voluntary health insurance. Yet little is known about the incidence and magnitude of such risk in developing countries, and even less about the formation of risk perceptions. Cross-sectional measurement of inter-household variation in medical expenditures confounds uncertainty faced by each household with differences in spending across households that are predictable from characteristics not fully observable in the data but known to the household (Flores and O'Donnell, 2013). Panel data of sufficient length to identify the stochastic properties of medical expenditures, which would feed into a measure of risk at the household level (Newhouse et al. 1989; van Vliet 1992; Feenberg and Skinner 1994; French and Jones 2004; Kowalski 2015), are rare; possibly even non-existent in a developing country context. Even if such data were available, using them to infer perceived medical expenditure risk would involve imposition of the assumption that expectations are formed rationally on the basis of all information available. The validity of this assumption has not been tested. In fact, very little is known about how individuals forecast their health expenditures and their ability to do so in any context (Breyer et al., 2012).

Improved knowledge of the formation of expectations regarding health care expenditure, perceptions of the associated financial risks and the degree to which the demand for insurance is related to such risks is essential for a better understanding of the functioning of insurance markets and social insurance programmes. Tests for adverse selection in health insurance based on the association between coverage and realized expenditures are plagued by the difficultly of disentangling selection from moral hazard (Chiappori, 2000). The relationship between forecast expenditure and subsequent enrolment potentially offers a more direct test.

This paper reports on the elicitation of subjective probabilities of medical expenditures in rural Ethiopia. It examines the extent to which expectations appear to be based on past realized expenditures, among other characteristics, and whether uptake of community based health insurance (CBHI) is related to both the mean and dispersion of the distribution of expected medical expenses. CBHI, which has been advanced as an affordable and feasible form of health insurance in low-income, informal rural economies (Preker and Carrin 2004), might be expected to be particularly vulnerable to adverse selection because of its voluntary nature and the small size of the risk pool (see Wang et al., 2006; Parmar et al., 2012). This apprehension is justified if individuals base their expectations and insurance purchases on determinants of medical expenditures that the insurer is either not able to observe or, as in the Ethiopian programme, premium is independent of individual risk. While rational agents will behave in this way, it is by no means obvious that unsophisticated consumers, with little or no experience of health insurance, perhaps little appreciation of factors that raise medical spending and possibly limited ability to predict their expenses, will do so. Particularly, but not only, in low-income contexts, the questions of how expectations of medical expenses are formed and utilized are very much open. We address these questions directly.

Besides the relevance of our analysis to the operation of voluntary health insurance in low-income settings -- in particular in Ethiopia, where nationwide scale-up of the pilot scheme examined here is planned -- the paper makes a modest methodological contribution. The high degree of risk exposure in low-income, rural settings has prompted experimentation with the elicitation of subjective probabilities of economic outcomes (e.g. Delavande 2008; Bellemare 2009; Giné et al 2009; Santos and Barrett 2011; Delavande and Kohler 2012; McKenzie et al. 2013). The emerging consensus is that it is feasible to elicit informative expectations data from low-income, less-educated populations (Attanasio 2009; Delavande et al. 2011; Delavande, 2014). To the best of our knowledge, this is the first study to elicit beliefs about future spending on health care in any setting - high- or low-income. Respondents were asked to report probabilities that their spending on medical care would exceed certain thresholds. Clearly, the information content of such data depends on the ability of individuals with limited educational attainment to understand relatively complex survey questions and to express beliefs consistent with the basic laws of probability. A central aim of the study is to establish whether it is possible to collect data on expectations that are valid in the sense of being logically consistent and plausibly informative of beliefs about future spending on health care.

We find that the bulk of the sample is able to respond sensibly to a seemingly abstract exercise of assessing the likelihood of future health scenarios and their associated medical expenses. Having verified the basic validity of the data, we make a distributional assumption that allows us to derive the first two moments of the distribution of expected medical expenditure for each household. Subsequently, we examine the information respondents utilise in forming expectations of medical expenditure, before evaluating the predictive value of expectations and, finally, assessing the extent to which health insurance enrolment is predicated on the expectation and perceived risk of medical expenses.

To preview our results, we find that the sample average of the second moment of expected medical expenditure is substantially smaller than the cross-sectional variance in realized medical expenditure, confirming that cross-sectional measures confound risk with predictable heterogeneity across households. Expected spending is positively related to past levels to an extent that exceeds the serial correlation in realized expenditure. This suggests that households underestimate volatility, which would reduce the perceived gains from insurance. Expected spending is positively correlated with realized spending in the period over which the forecast is made. After conditioning on observable covariates, expected expenditure still predicts realized spending (albeit weakly) suggesting that respondents hold some additional relevant information that is incorporated in their reported subjective probabilities.[2] However, there is little or no evidence that expectations influence the decision to take out health insurance, although plans to insure are positively related to the perceived dispersion of medical expenses.

The paper is organized as follows. Section 5.2 describes the context, including the CBHI pilot, and the sampling design, and elaborates on the manner in which the subjective probabilities of health payments were elicited. Section 5.3 assesses the validity of the expectations data. In section 5.4, we derive moments of expected medical expenditure and compare them with past expenditure and with realized spending during the expectation period. Section 5.5 examines factors associated with the formation of beliefs concerning the mean and dispersion of future health spending. Section 5.6 assesses the accuracy of expectations and the extent to which they add value in predicting future spending. Section 5.7 examines whether the distribution of expected expenditure is utilised in the decision to enrol in insurance. The final section offers concluding remarks.

## 5.2 Survey data and belief elicitation instrument

### 5.2.1 Context and sampling design

Three rounds of household panel data were collected in 16 rural districts located in four of the nine regions of Ethiopia (Tigray, Amhara, Oromiya, and SNNPR). These regions account for about 86 percent of the country's population (Population Census Commission, 2008). Within each district, the first survey round was fielded in six randomly chosen Kebeles (lowest administrative unit) in March-April 2011. In each of the 96 Kebeles, 17 households were randomly selected yielding a total of 1,632 households comprising 9,455 individuals. After the introduction of the CBHI scheme in 12 of the 16 districts in June-July 2011, two follow-up surveys of the same households, on which the bulk of the paper is based, were fielded in March-April 2012 (N=1599 households) and 2013 (N=1583).

Within the 12 districts in which the insurance scheme operates, enrolment is voluntary at the household level. Premia vary across regions but not across households within regions.[3] The benefit package is comprehensive including both outpatient and inpatient care with very few exclusions. There are no co-payments, provided higher levels of care are accessed through referral from a health center. Without a referral, households are liable for 50 percent of the cost of hospital treatment. By April 2012, the scheme had achieved an enrolment rate of around two-fifths of households residing in the targeted districts, and by April 2013 coverage had reached around one half.

### 5.2.2 Elicitation of expectations

A respondent, usually the head of the household or the spouse of the head, was asked about anticipated payments for health care and medicines over the next 12 months. The belief elicitation proceeds by first asking preliminary questions to fix the range of the distribution of the expectation and then asking the respondent to report the probability of exceeding thresholds within this range (Dominitz and Manski 1997; Manski 2004; Attanasio and Augsburg 2012). The specific questions used to determine the minimum and maximum amounts were:

> *Imagine that no member of your household contracts a* ***NEW serious illness or injury*** *in the next 12 months. In such a case what would be the* ***MINIMUM*** *amount of money your household would have to pay for health care and medicines (including transport costs) over the next 12 months?*

> *Imagine that at least one member of your household contracts a* ***NEW serious illness or injury*** *that requires treatment in a hospital in the next 12 months. In such a case what would be the* ***MAXIMUM*** *amount of money your household would have to pay for health care and medicines (including transport costs) over the next 12 months?*

The reference to a new illness is intended to ensure that long-standing health conditions that will continue to require treatment and medication are not overlooked in reporting the minimum and that the maximum refers to expenses that would be incurred were health to deteriorate markedly. The reference to hospital treatment in the maximum question is intended to prompt thought of the most expensive scenario.

After establishing the range, enumerators were instructed to compute three thresholds that divide the range into four equal intervals.[4] Respondents were then asked:

> *How likely is it that the amount your household will spend on health care and medicines (including transport costs) in the next 12 months will be greater than: [amount defined by each of three thresholds]?*
>
> **(see scale below which goes from 0 to 10 where 0 indicates no chance of happening and 10 indicates will definitely happen)** *[ruler shown].*

If the respondent was unsure but thought it was more likely that the household would spend more than the given threshold than not, then s/he was instructed to point somewhere between 0 and 10 but closer to 10 than 0 (and vice versa). Enumerators were instructed not to prompt for revision even if the responses did not seem sensible, e.g., because the reported likelihood of exceeding a higher threshold was greater than that reported for a lower threshold.

### 5.2.3 Covariates

The expectations questions were asked immediately after questions about the affordability of CBHI (for those enrolled) and after a series of questions about the incidence and economic consequences of illness and death in the household in the last 12 months. Respondents had therefore been primed to contemplate expenses that can arise from illness, injury and death. A preceding module recorded health care utilization and expenditures incurred. For each episode of illness experienced by any household member in the previous two months, the respondent was asked to report the type and quantity of ambulatory health care received and the payments made for consultation and diagnostics, medicine, transport and other associated health care costs. Additionally, all hospitalizations of household members in the previous 12 months were reported along with the costs incurred. The information on actual medical expenditure was recorded in all rounds of the survey, while the expectations were elicited in the last two rounds.

A health module asked the respondent to report for each household member his or her general health status (excellent-very poor), chronic illness (defined as symptoms lasting for more than 30 days), paralysis, limitations in performing activities of daily living and a variety of acute illnesses experienced in the last two months. In addition to the rich data on expectations, medical expenses and health, the surveys contain information on consumption expenditure, assets, occupation, housing conditions and amenities, demographics, education, religion, social capital and access to facilities. As is clear from Table 5.1, the sample households are predominantly agricultural, have very low levels of education and about a quarter are chronically food insecure which is indicated by their participation in a government safety net programme.[5]

***Table 5.1***
*Sample means of basic household characteristics in 2012*

| | |
|---|---|
| Household Head | |
| Male | 0.84 |
| Age (years) | 47.2 |
| No education | 0.45 |
| Farmer | 0.84 |
| Muslim | 0.27 |
| Household | |
| Number of persons | 5.8 |
| Enroled in CBHI | 0.31 |
| Someone in hhold reports poor/very poor health | 0.13 |
| Time to nearest health centre (minutes) | 63 |
| Covered by safety net programme | 0.23 |
| Number of observations | 1599 |

*Notes: The CBHI enrolment rate given here is for the whole sample and so is less than the two-fifths quoted in the text which refers to coverage in the districts in which CBHI is available.*

## 5.3 Validity of the expectations data

Our first objective is to establish whether it is feasible to elicit informative data on expectations of medical expenditures in the context of a poor rural economy. This section examines the validity of the data by considering, *seriatim,* response rates, illogical responses and response clustering.

### 5.3.1 Response rates

Only 19 of 1,599 households surveyed in 2012 did not respond to all of the expectations questions, and there were only two such households in 2013 (Table 5.2). Almost all of these incomplete responses did not report the minimum and/or maximum (12), or gave zero values for both (7), and subsequently were not asked to report subjective probabilities. Only one respondent in each wave gave valid minimum and maximum values yet refused to answer the probability questions.

***Table 5.2***
*Expectations: non-response, enumerator errors & illogical responses*

| | ***2012*** | ***2013*** |
|---|---|---|
| **Total number of observations** | **1599** | **1583** |
| Non response | 19 | 2 |
| Enumerator error in calculation of thresholds | 229 | 88 |
| Those of which resulted in wrong ordering of thresholds | 38 | 30 |
| **Total usable observations** | **1542** | **1551** |
| Illogical responses | | |
| One violation of monotonicity | 66 | 127 |
| Two violations of monotonicity | 65 | 100 |
| All reported probabilities zero | 46 | 28 |
| Observations with illogical responses | 177 | 255 |
| **Total observations with logical responses** | **1365** (85.4%) | **1303** (82.3%) |

*Notes: Observations are household respondents. `Non-response' includes those not giving a minimum and/or maximum amount of health spending (11 in 2012, 1 in 2013), zero for both the minimum and maximum (7 in 2012, zero in 2013) and no probability despite providing a minimum and maximum (1 in both 2012 and 2013). 'Enumerator error in calculation of thresholds' refers to errors in computation of k=(max-min)/4, A=min+k, B=A+k or C=B+k. 27/32 (2012) and 33/57 (2013) enumerators made such errors. '….wrong ordering of thresholds' refers to violation of max>C>B>A>min. 18/32 (2012) and 23/57 (2013) enumerators made such errors. Total usable observations = 1599-19-38 in 2012 and 1583-2-30 in 2013. One (two) violation of monotoncity corresponds to P(X>A)<P(X>B) or (and) P(X>B)<P(X>C), with A<B<C by construction. Total observations with logical responses in 2012 and 2013 respectively = 1542-177 and 1551-255.*

A non-response rate of only 0.7% is reassuring, suggesting that the exercise is not too abstract. But mere participation is no guarantee that responses contain information on beliefs held with respect to future spending on health care. A basic requirement for the data to be informative is that the expenditure reported in the negative scenario, that is, onset of new serious illness/injury that required hospitalization should not be lower than the expenditure reported for the most positive scenario, that is, no onset of any new illness/injury. Enumerators were instructed to prompt respondents to revise the amounts reported if this occurred, which did happen relatively frequently.[6] 364 households (23%) in 2012 and 314 households (20%) in 2013 were prompted to make a revision, suggesting a degree of difficulty in recognizing the brief scenarios as indicative of the least and most expensive outcomes with respect to medical expenditures.[7] Those prompted to revise their max/min values were more likely to report logically inconsistent probabilities (p value=0.000).

Enumerators made mistakes in calculating the intended evenly-spaced thresholds for 229 households (15%) in 2012 and 88 households (6%) in 2013 (Table 5.2). These errors do not emanate only from a few enumerators – in 2012 more than four-fifths of the enumerators made at least one mistake while this goes down to less than three-fifths in 2013. They are not fatal for the belief elicitation exercise provided that the thresholds calculated are in increasing order, even if they are not evenly spaced. This condition is violated only for 38 households in 2012 and 30 households in 2013.

In total, we lose 57 out of 1599 observations in 2012 and 32/1583 in 2013 due to non-response or calculation errors. Households dropped are smaller, poorer and more likely to be headed by a female, to forgo health care when sick and to have a member with some sort of disability (Appendix Table A5.1).

### 5.3.2 Illogical responses

Consistency of responses with the axioms of probability requires that the reported probabilities of incurring health expenditure (X) in excess of a series of increasing thresholds (A<B<C) satisfy monotonicity: $\mathrm{P(X > A) \geq P(X > B) \geq P(X > C)}$. Responses that do not satisfy this condition are labelled illogical. Of the usable observations, 131 (8.5%) in 2012 and 227 (14.6%) in 2013 violated monotonicity at least once (Table 5.2). A further 46 and 28 in 2012 and 2013, respectively, reported zero probability of spending more than all three thresholds, which we also consider an error since the same respondents report a maximum possible expenditure in excess of all three thresholds. In total, 177 respondents in 2012 (11.5%) and 255 in 2013 (16.4%) reported probabilities that are logically inconsistent. This is higher than the 4 percent rate of logical response errors found by Attanasio and Augsburg (2012) in their study of subjective income expectations in rural India using a similar instrument but is comparable to Dominitz and Manski's (1997) finding of a 10 percent error incidence for subjective expectations of income in Wisconsin.[8]

The higher error incidence compared with the Indian study may reflect greater difficulty in conceiving contingencies that lead to variation in medical expenses as compared to considering the likelihood of reaching certain levels of income.[9]

Similar to those excluded because of non-response or enumerator errors, households providing illogical responses are more likely to be poorer, smaller, less healthy and more likely to forgo health care for economic reasons (Appendix Table A5.1). They are also less likely to be enrolled in the health insurance scheme and to be engaged in agricultural activities as their main occupation.

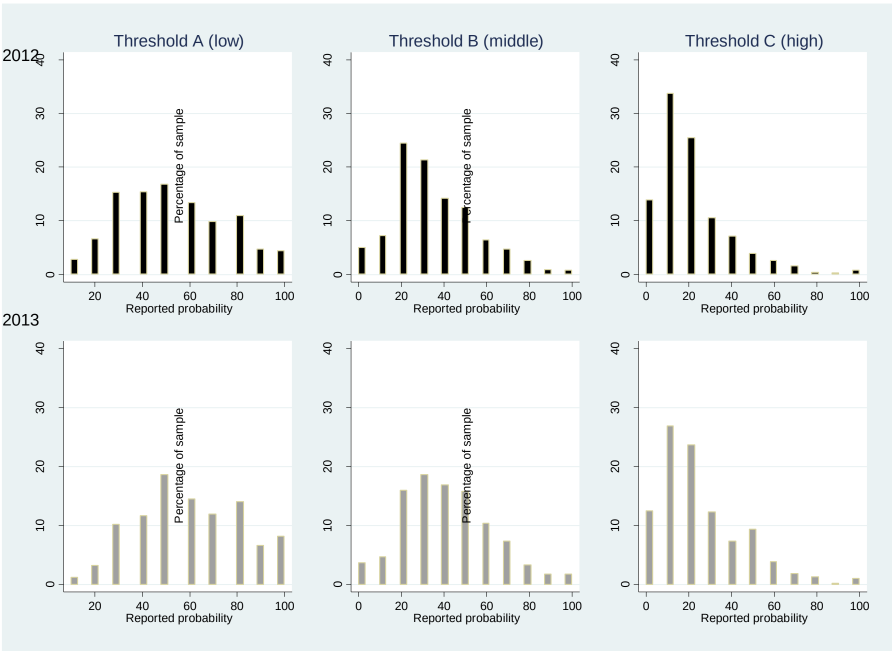
### 5.3.3 Distribution of responses

Distributions of the reported probabilities for each of the thresholds are presented in Figure 5.1. Two observations are particularly noteworthy. First, there is no bunching at focal responses of 0%, 50% or 100%, which is often a feature of subjective probability data (Kleinjans and van Soest 2014). The most likely explanation is our use of a 0-10 reporting scale (subsequently transformed), rather than 0-100. While the narrower scale would be anticipated to result in less variation, the lack of bunching suggests that the loss of information may not be so severe.

The second observation is that there is a clear shift in the mass of the probability distribution from right to left as we move from the lowest to the highest threshold. To an extent, this is inevitable since observations that violate monotonicity have been dropped. But the degree of the shift in the distributions is indicative of respondents understanding the question and reporting substantially lower, on average, probabilities as the threshold is raised.

Overall, the high response rate, the majority of usable, logically consistent responses (85 percent in 2012 and 82 percent in 2013), the lack of bunching and the anticipated shift in the mass of the distribution as the threshold is raised suggests that the bulk of the sample is able to respond sensibly to a seemingly abstract exercise of contemplating and assessing the likelihood of future health scenarios and their associated medical expenses. This lends support to interpretation of the responses of each household as points on its cumulative distribution function of expected medical expenditure.

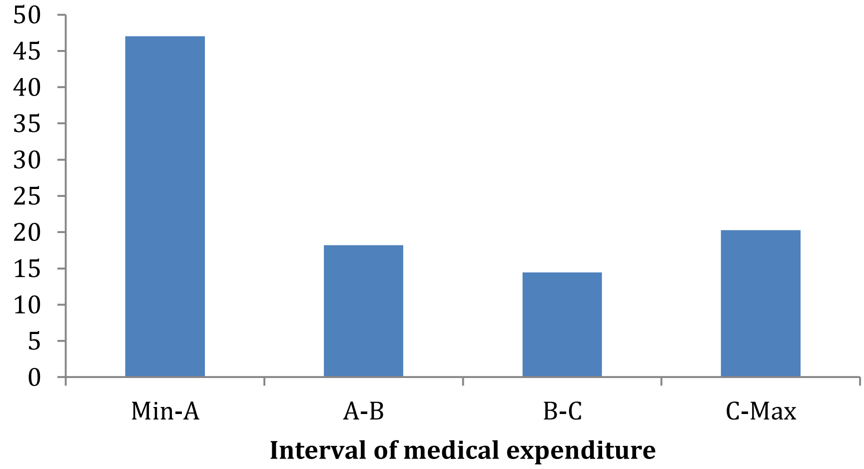
***Figure 5.1***
*Distributions of reported probabilities of medical spending exceeding various thresholds*




## 5.4 Distributions of expected medical expenditure

Figure 5.2 shows the reported probability that medical expenditure falls within each of the four equally-spaced, household-specific intervals averaged across households in the 2012 survey.[10] On average, the responses show that the probability of health expenditure falling in in the lowest interval is the highest. Since, as will be confirmed below, many households incur no medical expenses, this suggests some consistency between the distribution of expected and actual expenditures. The average probability mass falls over the next two intervals, before rising slightly for the top interval. On average across households, the distribution of forecast medical expenditures broadly resembles the right-skewed distribution familiar for actual medical expenditures, although the reason for the increase in density at the top of the distribution is not obvious. It may be that respondents become anchored to the maximum value reported.[11]

***Figure 5.2***
*Sample means of reported probabilities of medical expenditure lying in household-specific intervals, 2012 (N=1365)*




**Notes:** *A=min+k, B=A+k and C=B+k, where k=(max-min)/4. P(X>A), P(X>B) and P(X>C), where X is medical expenditure, are reported directly for each household, as are min and max. Probability of X lying in each interval is computed from these reported probabilities. Sample restricted to observations for whom correct order of thresholds calculated and responses are logically consistent.*

### 5.4.1 Moments of the expected medical expenditure distributions

We assume that a piecewise uniform distribution provides a reasonable approximation to the underlying probability distribution for each household and use this, along with the elicited subjective probabilities, to compute the first and second moments of the distribution of expected health expenditure in the next 12 months for each household.[12] We do the same for the distribution of the logarithm of expenditures.

***Table 5.3***
*Sample statistics of expected and realized medical expenditure, 2012 (ETB)*

| | Cross-section statistics | | | | | |
|---|---|---|---|---|---|---|
| | *Mean* | *Std. dev.* | *Min.* | *Median* | *Max.* | *Obs.* |
| Expected Expenditure (t+1) | | | | | | |
| Mean | 461 | 562 | 2.40 | 305 | 6375 | 1365 |
| Standard deviation | 173 | 256 | 1.08 | 101 | 3320 | 1365 |
| Coeff. of variation | 0.35 | 0.18 | 0.02 | 0.34 | 1.08 | 1365 |
| Realized Expenditure (t) | | | | | | |
| Simple extrapolation | 393 | 1441 | 0 | 0 | 19830 | 1365 |
| Regression extrapolation | 390 | 1047 | ~0 | 120 | 16476 | 1355 |
| If realized expenditure >0 | | | | | | |
| Mean expected expenditure (t+1) | 520 | 641 | 21 | 326 | 6375 | 398 |
| Realized expenditure (t) | 1349 | 2418 | 6 | 480 | 19830 | 398 |

**Notes:** *Simple and regression extrapolation of realized expenditures refer to method of estimating annual spending on outpatient care from reported expenditure in past two months, as explained in text. Sample size for regression extrapolation is slightly smaller due to missing values on covariates. ETB = Ethiopian Birr, US$1=ETB 17.42 (April 2012)*

The top panel of Table 5.3 provides sample summary statistics of parameters of the household-specific distribution of expected medical expenditure derived from the probabilities reported in the 2012 survey (see Appendix Table A5.2 for 2013). The mean of expected annual expenditure (i.e. the first moment of the expectation distribution) ranges from ETB 2.40 (US$ 0.14) to ETB 6375 (US$ 365.97), with a sample mean of ETB 461 (US$ 26.41). Comparison with the distribution of realized expenditures in the *prior year* is complicated by the fact that spending on outpatient care is reported for a period of two months preceding the survey. We approximate annual expenditure by *simple extrapolation,* i.e. multiplying outpatient expenditure by six and adding the result to inpatient expenditure reported for the past twelve months. While this provides a credible estimate of mean annual expenditure across the sample, it will overestimate the inter-household variance. Therefore, we also predict outpatient expenditure in the last two months based on a Poisson regression (Jones, 2011) of reported expenditure on characteristics of the household that do not reflect acute illness and multiply the prediction by six before adding inpatient expenditure (referred to in Table 5.3 as *regression extrapolation*).[13] This gives the same sample mean as the simple extrapolation method but a smaller variance, which in this case is underestimated.[14]

The sample mean of the mean expected expenditure is about one-sixth greater than the mean of realized expenditures. The discrepancy appears to be attributable to the large difference in the propensity of zero expenditures. Despite the large proportion of households with no reported spending on health care (71% by the simple extrapolation method), respondents seldom contemplate making no payments even when told to think of a scenario in which no new serious illness or injury is contracted and health spending is at a minimum.[15] Restricting attention to households that incurred medical expenditures, the sample mean of these positive expenditures is 2.7 times the mean of the expected expenditures. This difference partly arises from the simple extrapolation of two-monthly expenditures on outpatient care, which will greatly overestimate annual expenditures for some households. The median of realized (positive) expenditure is closer to that of expected expenditure, although the difference is still substantial.

It is important to emphasise that the sample distribution of expected expenditures should not resemble that of realized expenditures. The former is a distribution of expectations, while the latter is a distribution of stochastic outcomes. The range and standard deviation of realized expenditures should be, and are, much greater than the corresponding sample statistics for the expected expenditure.

For the purpose of gauging exposure to medical expenditure risk, comparison of the standard deviation of expected medical expenditure with the cross-sectional standard deviation of realized expenditure is of greater interest than comparison of the mean of expected expenditure with the sample mean of realized expenditures. The sample mean of the standard deviation of forecast expenditure is only one-sixth of the cross-section standard deviation of realized expenditure based on the regression extrapolation approach, and an even lower proportion of the estimate using simple extrapolation of outpatient expenditures. On average across the sample, the household-specific standard deviation of expected expenditure is less than the mean (mean coefficient of variation is a little more than a third), while, as is common with cross-section data on health care costs (e.g. Van Doorslaer et al, 2007), the standard deviation across households is substantially larger than the sample mean.

These comparisons suggest there is substantial overestimation of risk exposure using measures based on cross-sectional variance. Such measures confound risk with predictable heterogeneity across households. Measures of dispersion in the distribution of expected expenditure do not. They capture perceptions of risk exposure, at least to the extent that risk is interpreted as the variability one faces in a stochastic outcome. The discrepancy between the two approaches to measuring medical expenditure risk would be substantially reduced by examining the cross-sectional variation in realized expenditures conditional on determinants of spending that are observable in the data (Flores and O'Donnell, 2013). But not all predictors that are known to the household are likely to be documented in the data, such that cross-sectional variance (of residuals) is still likely to overestimate risk perceived by the household and, consequently according to theory, its demand for single-period insurance.

### 5.4.2 Correlation between expected and past medical expenditure

The degree to which medical expenditures display persistence over time and the extent to which this is taken into account in the formation of expectations about future medical spending are of considerable importance to the operation of health insurance markets (Breyer et al. 2012). We begin to address these issues by examining simple correlations before turning to regression models.

The serial correlation between actual health expenditure in ETB money values incurred in consecutive years is small and not significantly different from zero for either pair of years (Table 5.4, top panel). The correlation is even lower for expenditure on inpatient care, but it is not significant for spending on outpatient care either. These correlations are considerably smaller than those obtained for health care costs in Europe and the US (see Breyer et al. 2012 for a review).[16, 17] One reason for this difference is that we have data on out-of-pocket payments (including transport costs), not health care costs, and because spending on outpatient care is reported only for the last two months we cannot compute the correlation across years of annual expenditure. Month-to-month fluctuations in spending will lower the correlation in outpatient expenses incurred over two periods of two months separated by one year relative to the correlation of annual expenditures over consecutive years.[18, 19]

***Table 5.4***
*Correlation between realized medical expenditure in consecutive years*

| | 2011-2012 | 2012-2013 |
|---|---|---|
| ETB Amounts | | |
| Full sample | | |
| Total | 0.033 (0.218) | 0.020 (0.499) |
| Outpatient | 0.030 (0.273) | 0.015 (0.619) |
| Inpatient | 0.001 (0.976) | 0.007 (0.812) |
| Censored at 99th percentile of positive expenditures | | |
| Total | 0.048 (0.074) | 0.027 (0.370) |
| Outpatient | 0.054 (0.045) | 0.013 (0.656) |
| Inpatient | 0.001 (0.976) | 0.007 (0.812) |
| Logs | | |
| Total | 0.122 (0.000) | 0.130 (0.000) |
| Outpatient | 0.129 (0.000) | 0.105 (0.000) |
| Inpatient | 0.058 (0.033) | 0.006 (0.838) |

*Notes: Total expenditure is computed by simple extrapolation method. Middle panel shows correlations with amounts above the 99th percentile of positive expenditures replaced with that percentile value. This censoring is done separately for each year and each distribution of total, outpatient and inpatient expenditure. p-value for test of zero correlation in parenthesis. Data in 2012 and 2013 are restricted to the sample with logical responses to expectations questions as detailed in Table 5.2.*

The serial correlation between actual health expenditure in ETB money values incurred in consecutive years is small and not significantly different from zero for either pair of years (Table 5.4, top panel). The correlation is even lower for expenditure on inpatient care, but it is not significant for spending on outpatient care either. These correlations are considerably smaller than those obtained for health care costs in Europe and the US (see Breyer et al. 2012 for a review).[20,21] One reason for this difference is that we have data on out-of-pocket payments (including transport costs), not health care costs, and because spending on outpatient care is reported only for the last two months we cannot compute the correlation across years of annual expenditure. Month-to-month fluctuations in spending will lower the correlation in outpatient expenses incurred over two periods of two months separated by one year relative to the correlation of annual expenditures over consecutive years.[22, 23]

Serial correlation is partly reduced by extremely high expenditures in one year that are not repeated. Censoring expenses at the 99th percentile of the distribution of positive expenditures increases the magnitudes of the correlations and results in two becoming significant (Table 5.4, middle panel). The distortionary effect of extreme amounts is also evident from the fact there is clear serial correlation in the logarithm of expenditure, particularly for spending on outpatient care (bottom panel).

A second potential explanation for the low serial correlation is the much lower relative burden of chronic disease in Ethiopia compared with high-income countries.[24] Notwithstanding the limitations arising from the two-month recall period for outpatient expenses, the apparently high degree of volatility in medical expenses would suggest that potential gains from risk pooling are substantial.

Table 5.5 shows correlations between expected and realized medical spending. In the second and third survey rounds, the respondent reported subjective probabilities for spending anticipated in the year ahead and actual expenditures incurred over the last year/two months. In the first round, only realized spending was reported. Using the responses over all three rounds, we can examine the correlation between expected expenditure for the year ahead and actual spending up to three years previous.[25] All correlations are positive. The one between expectations and three year lagged actual spending is the smallest and is not significant. For both survey rounds, expectations are more closely correlated with spending over the last year than with spending in the year prior to the last (but this decline is statistically significant only for the later survey round). This suggests that expectations are formed based on more recent information. The positive correlations are not simply driven by the large proportion of households incurring no health expenditure expecting to spend little in the future. In fact, when attention is restricted to households with positive past levels of spending, the correlations increase (Table 5.5, bottom panel).

***Table 5.5***
*Correlations between expected and realized medical expenditure*

| Realized expenditure | ***Expenditure expected in t+1*** | |
|---|---|---|
| | ***t=2012*** | ***t=2013*** |
| t-2 | N/A | 0.043 |
| t-1 | 0.128*** | 0.069** |
| t | 0.136*** | 0.221*** |
| t+1 | 0.138*** | N/A |
| If realized exp. >0 | | |
| t-2 | N/A | 0.045 |
| t-1 | 0.143*** | 0.089* |
| t | 0.192*** | 0.334*** |
| t+1 | 0.186*** | N/A |

*Notes: Realized expenditure calculated by multiplying outpatient expenditure reported for last two months by six and adding result to inpatient expenditure reported for the last year. N/A - data on realized expenditure are not available. *** p<0.01, ** p<0.05, * p<0.1*

The significant positive correlation of expectations with past expenditure is in contrast to the absence of serial correlation in actual spending (at least when measured in money values, not logs). While we must acknowledge again that our ability to estimate the latter is limited by the two-month recall period for outpatient expenses, this discrepancy is at least indicative of adaptive expectations, rather than rational expectations, with the degree of persistence being overestimated. However, expectations are not entirely inaccurate. There is a significant positive correlation between the expectation for the year ahead derived from the subjective probabilities reported in 2012 and the expenditure that materialised over the following year (Table 5.5, 1$^{st}$ column, 4$^{th}$ row). This indicates that households are, at least to some extent, able to predict their future spending on medical care.

## 5.5 Formation of medical expenditure expectations

### 5.5.1 Predictors of the mean of expected medical expenditure

In Table 5.6, we present least absolute deviations (LAD) and least squares regressions of the mean of log expected expenditure on past realized expenditures and other household characteristics potentially relevant to the formation of expectations. The estimates may be interpreted as best linear predictions, revealing how expectations correlate with observable characteristics (Dominitz, 2001). Past outpatient and inpatient expenditures incurred in the year in which expectations were elicited as well as expenditures incurred in the previous year are entered separately because it is plausible that differences in the nature of health conditions that result in outpatient and inpatient expenditures lead to differential weighting of them in the formation of expectations. The specification is consistent with adaptive expectations, which implies that expected spending is a weighted average of realized spending in previous periods (Nerlove, 1958), although we do not claim to be testing this hypothesis.[26] Inclusion of the lagged value of outpatient expenditure is particularly appropriate because of the two-month reference period that results in a partial measure of the information on such spending the household may utilise to predict spending in the coming year. Besides past expenditures, the regressions include indicators of: i) health (illness, sensory impairment, disability, health self-assessed as poor/very poor and a recent death in the household); ii) socioeconomic status (wealth represented by quintile groups of a composite index of assets and housing conditions, participation in a safety net programme, possession of a savings account, occupation and education); iii) health care coverage/access (CBHI enrolment, reported forgone care when sick and time to nearest health center); iv) experience of an economic/crime/conflict/natural shock in past year; and, v) household size and demographics. Definitions and means of the covariates are provided in the Appendix, Table A5.3. The regressions presented in Table 5.6 are estimated from the pooled 2012 and 2013 observations.[27]

The ordinary least squares (OLS) predictions account for around 30 percent of the variability in the mean of expected expenditure across the sample indicating a good deal of systematic variation. The reported expected medical expenditures are very far from being pure noise.

The pooled LAD and OLS estimates reveal that inpatient expenditure in the last year and outpatient expenditure both in the last two months and in the two months preceding the previous survey are all statistically significant predictors of the mean of (log) expected medical expenditure in the year to come. The latter is not significantly associated with expenses incurred on inpatient care in the year preceding the last. This may be because inpatient treatment is received for more acute conditions while outpatient expenditures include medication that can be taken for more chronic conditions. Using the usual approximation, a 1% increase in inpatient expenditure over the last year is associated with a 0.14% increase in the expectation of total medical expenditure in the coming year. The elasticity with respect to outpatient expenditure in the last two months is smaller, which is to be expected given the discrepancy in the reference periods.[28] But expectations are also positively related to spending on outpatient care in the two months prior to the last survey, which is consistent with respondents forming expectations on the basis of average spending over a number of periods. The LAD estimates for outpatient expenses are a bit lower than the OLS estimates while the coefficients for inpatient spending are robust.

Given the magnitude of expenditures on inpatient care, one expects that households can remember and report them accurately. Even if errors are made, provided the reported expenditures are those utilised in the formation of expectations of future spending, there will be no bias in the estimate of the association between expected and (perceived) past expenditure. However, expenditures on ambulatory care and medicines reported for the last two months are a noisy indicator of actual expenditures on these items in the last year. We deal with this by instrumenting household reported outpatient expenditure in the two months before each survey with respective mean outpatient expenditure in the Kebele in which the household is located. Two stage least squares coefficients reported in the third column of Table 5.6 show substantial increases in the coefficients on each of the two instrumented expenditure variables, which become comparable to the elasticity estimated for inpatient expenditure in the last year. Most of the coefficients of the other covariates remain similar in magnitude and significance to the OLS estimates.

Expected spending on medical care appears to be very closely correlated with ability to pay. On the basis of the OLS estimate, the richest quintile spends two-thirds more on medical care in the coming year than the poorest fifth of households. Households in which the head has some form of education expect to spend 8.4% more than those without any education. Expected spending is negatively associated with household participation in a safety net programme and whether a household has forgone care. Although neither of these relationships is individually significant[29], both are consistent with the general pattern in the estimates which suggests that households expect to spend what they can afford.

Enrolment in the CBHI scheme is positively but not significantly correlated with expected medical spending. The point estimate suggests that households that require more time to travel to a health center expect to spend more. Although this is significant only for OLS, it is consistent with the inclusion of transport costs in the expenses respondents are instructed to report. Of the health variables, only illness with symptoms that have lasted for at least one month is significantly correlated with the mean of log expected medical expenditure. This variable loses significance when outpatient expenditure in the last two months is instrumented, which is consistent with both providing information on health that is utilised in the formation of expectations of medical expenses.[30] Jointly the health variables are significant (p-value=0.055 for OLS). Households that reported having experienced a negative shock due to the local economy, weather, crime or conflict in the last year expect to incur greater expenditure on medical care in the coming year. Notwithstanding the fact that there has been some control for health, the most likely explanation would appear to be illness or injury as the result of such an event. The demographic composition of the household appears to matter (jointly significant across all estimators). The coefficients are not presented but expected expenditure is lower in households that have a larger share of elderly (60+) females relative to all other demographic groups.

**Table 5.6**
*Pooled regressions of the Mean of Log Expected Medical Expenditure*

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | LAD | | OLS | | 2SLS | |
| Ln(outpatient expense) t | 0.0170* | (0.00986) | 0.0225*** | (0.00762) | 0.101** | (0.0503) |
| Ln(outpatient expense) t-1 | 0.0259** | (0.0110) | 0.0418*** | (0.00876) | 0.130*** | (0.0419) |
| Ln(inpatient expense) t | 0.142*** | (0.0305) | 0.141*** | (0.0219) | 0.129*** | (0.0251) |
| Ln(inpatient expense) t-1 | 0.0159 | (0.0299) | 0.00439 | (0.0222) | -0.0126 | (0.0244) |
| Someone in household experienced: | | | | | | |
| Illness > 30 days | 0.228** | (0.0886) | 0.173** | (0.0754) | 0.0585 | (0.0948) |
| Sensory impairment | 0.0279 | (0.0775) | 0.00896 | (0.0613) | 0.00626 | (0.0617) |
| Paralysis/mobility issues | -0.0547 | (0.0741) | -0.0163 | (0.0586) | -0.0463 | (0.0628) |
| Poor/very poor health | 0.118 | (0.0731) | 0.0826 | (0.0729) | -0.0264 | (0.0828) |
| Death in last year | 0.0583 | (0.193) | 0.149 | (0.129) | 0.0967 | (0.140) |
| 2nd poorest assets quintile group | 0.153* | (0.0893) | 0.208*** | (0.0592) | 0.199*** | (0.0621) |
| Assets quintile 3 | 0.269*** | (0.0965) | 0.298*** | (0.0594) | 0.291*** | (0.0606) |
| Assets quintile 4 | 0.287*** | (0.0909) | 0.404*** | (0.0635) | 0.375*** | (0.0690) |
| Richest assets quintile group | 0.531*** | (0.102) | 0.669*** | (0.0713) | 0.621*** | (0.0760) |
| Covered by safety net programme | -0.154** | (0.0635) | -0.0608 | (0.0597) | -0.0494 | (0.0658) |
| Has bank account | 0.103 | (0.0664) | 0.0916 | (0.0677) | 0.0799 | (0.0680) |
| Non-agricultural employment | 0.212 | (0.149) | 0.162 | (0.129) | 0.137 | (0.126) |
| Educated head | 0.115** | (0.0511) | 0.0842** | (0.0389) | 0.0725* | (0.0416) |
| CBHI enrolled | 0.0738 | (0.0514) | 0.0423 | (0.0431) | 0.0607 | (0.0419) |
| Forgone care when sick | -0.133 | (0.153) | -0.116 | (0.119) | -0.0911 | (0.125) |
| Minutes to nearest health center | 0.000766 | (0.00067) | 0.000778* | (0.00047) | 0.000702 | (0.00049) |
| Shock | 0.151*** | (0.0474) | 0.106** | (0.0500) | 0.103** | (0.0513) |
| Ln(household size) | 0.0870 | (0.0935) | 0.000928 | (0.0606) | -0.0635 | (0.0697) |
| Year 2013 | 0.234*** | (0.0442) | 0.298*** | (0.0690) | 0.331*** | (0.0647) |
| Constant | 3.776*** | (0.267) | 3.588*** | (0.200) | 3.670*** | (0.208) |
| Observations | 2,631 | | 2,631 | | 2,631 | |
| R2/Pseudo R2 | 0.159 | | 0.298 | | | |
| F-test of joint significance (p-values): | | | | | | |
| All variables | 0.000 | | 0.000 | | 0.000 | |
| Health variables | 0.010 | | 0.055 | | 0.833 | |
| Age-sex composition | 0.036 | | 0.010 | | 0.003 | |

*Notes: Regressions also include the share of household member in ten gender specific age groups and district dummies. Standard errors in parentheses: corrected for clustering at Kebele level for OLS and 2SLS; bootstrap standard errors with 200 repetitions for LAD. *** p<0.01, ** p<0.05, * p<0.1*

### 5.5.2 Revisions to the mean of expectations

The fact that the means of the distributions derived from reported subjective probabilities correlate with past realized expenditures, ability to pay proxies and health provides grounds to interpret these means as expectations of future spending on medical care. However, the associations could arise from confounding factors correlated with both the reporting of subjective probabilities and the regressors. We deal with time invariant confounders by estimating in first differences. If the associations are preserved, this would provide stronger evidence that the data contain information on expectations that are revised in response to changes in realized expenditures, economic circumstances and health.

Descriptive statistics of the cross-sample distribution of changes (between the 2012 and 2013 surveys) in the means of the distributions of the mean expected medical expenditure and of the changes in realized inpatient and outpatient expenditures are provided in Table 5.7. On average, across the sample, the mean of expected expenditure is revised upward. This is also apparent from the coefficients on the year dummy in Table 5.6. The correlation coefficient between change in the mean of expected expenditure and change in realized outpatient expenditure is 0.061. The respective correlation with change in realized inpatient expenditure is 0.075. Both are statistically significant at 5% level.

***Table 5.7***
*Sample statistics of changes in the mean of expected and realized medical expenditure, 2012-2013 (ETB)*

| | ***Cross-section statistics*** | | | | | |
|---|---|---|---|---|---|---|
| | ***Mean*** | ***Std. dev.*** | ***Min.*** | ***Median*** | ***Max.*** | ***Obs.*** |
| Change in: | | | | | | |
| Mean of expected exp. | 220 | 920 | -4625 | 79 | 10050 | 1122 |
| Realized inpatient exp. | 15 | 644 | -5000 | 0 | 12000 | 1122 |
| Realized outpatient exp. | -3 | 325 | -3305 | 0 | 5800 | 1122 |

***Notes:*** *Outpatient expenditure is for two months. Sample is restricted to those reporting logical responses to expectations questions in both rounds.*

The mean of log expected medical expenditure continues to be positively and significantly associated with realized outpatient and inpatient expenditures (Table 5.8, column 1). The mean expected spending does appear to be revised upward when actual spending in previous periods increases. The coefficient on both past outpatient expenditures increase somewhat relative to the levels estimates while that on inpatient expenditure in the last year falls. Inpatient expenditure in the previous to last year remains insignificant. Instrumenting the changes in outpatient spending with the Kebele specific mean changes results in increases in the outpatient coefficients. While most of the significant predictors in the models estimated in levels are no longer statistically significant, we continue to find that better-off households (in terms of asset quintiles and those with bank saving accounts) expect higher expenditure.

As a further robustness check we altered the manner in which expected expenditure is defined. Rather than using the mean of log expected expenditure, which is derived under the assumption that the distribution is piece-wise uniform, we took the log of the mid-point of the reported minimum and maximum expected health expenditure.[31] Regression results in both levels and differences are similar to those presented in Tables 5.6 and 5.8 (see Appendix Table A5.5).[32]

### 5.5.3 Predictors of the standard deviation of expected medical expenditure

We now examine whether there is systematic variation in the standard deviation of log expected medical expenditure that could possibly be interpreted as differences in exposure to medical expenditure risk. LAD, OLS and 2SLS estimates in levels for essentially the same empirical specification as utilised for explanation of the mean of the expectation are presented in Table 5.9.[33] These reveal much less systematic variation in the standard deviation, although predictions from the OLS estimates still account for ten percent of the cross-sample variability. Few of the covariates are statistically significant irrespective of the estimator. The standard deviation is predicted to be five percent lower in households that experienced a death in the preceding year. Possibly, this could be because the departure of a frail relative reduces uncertainty over medical expenses. Better-off households in the top sixty percent of the wealth distribution report expectations that imply a 4-7 percent greater standard deviation of medical expenditure. This is much less than the increase in the mean expectation with wealth, implying that the coefficient of variation falls with wealth. Beneficiaries of the safety net program also report a 3 percent greater standard deviation of expected medical expenditure.

The standard deviation of expected medical expenditures does not appear to be associated with past realizations of expenditure, health or access to health facilities. This may indicate that perceived exposure to medical expenditure risk does not vary with these factors. While the location of the distribution of medical expenditures would be anticipated to vary with these factors, their implications for dispersion are indeed less obvious. It could be that the data reflect this.

**Table 5.8**
*Regressions of the Mean of Log Expected Medical Expenditure (first differences)*

| | (1) | | (2) | |
|---|---|---|---|---|
| | OLS | | 2SLS | |
| Ln(outpatient expense) t | 0.0386** | (0.0148) | 0.254*** | (0.0778) |
| Ln(outpatient expense) t-1 | 0.0507*** | (0.0155) | 0.283*** | (0.0891) |
| Ln(inpatient expense) t | 0.115** | (0.0466) | 0.120** | (0.0516) |
| Ln(inpatient expense) t-1 | -0.0350 | (0.0475) | -0.0586 | (0.0570) |
| Someone in household experienced: | | | | |
| Illness > 30 days | 0.0490 | (0.136) | 0.0203 | (0.139) |
| Sensory impairment | -0.0277 | (0.0962) | -0.0445 | (0.110) |
| Paralysis/ mobility problem | 0.0674 | (0.0863) | 0.0477 | (0.0872) |
| Poor/very poor health | 0.141 | (0.114) | 0.00600 | (0.122) |
| Death in last year | 0.146 | (0.238) | 0.174 | (0.273) |
| 2nd poorest assets quintile group | -0.00513 | (0.0955) | -0.0708 | (0.0975) |
| Assets quintile 3 | 0.0893 | (0.115) | -0.00940 | (0.129) |
| Assets quintile 4 | 0.174 | (0.120) | 0.123 | (0.132) |
| Richest assets quintile group | 0.562*** | (0.148) | 0.521*** | (0.157) |
| Covered by safety net programme | 0.176 | (0.165) | 0.252 | (0.171) |
| Has bank account | 0.186* | (0.111) | 0.265** | (0.110) |
| Non-agricultural employment | 0.182 | (0.232) | 0.0940 | (0.244) |
| Educated head | 0.137 | (0.0849) | 0.102 | (0.0933) |
| CBHI enrolled | 0.0161 | (0.0787) | 0.0445 | (0.0746) |
| Forgone care when sick | -0.114 | (0.142) | -0.155 | (0.174) |
| Minutes to nearest health center | 0.000817 | (0.00102) | 0.000813 | (0.00113) |
| Shock | 0.0943 | (0.0760) | 0.107 | (0.0789) |
| Ln(household size) | 0.365 | (0.248) | 0.446 | (0.273) |
| Constant | 0.328*** | (0.0687) | 0.387*** | (0.0616) |
| Observations | 1,097 | | 1,097 | |
| R2 | 0.079 | | | |
| F-test of joint significance (p-values): | | | | |
| All variables | 0.000 | | 0.000 | |
| Health variables | 0.636 | | 0.977 | |
| Age-sex composition | 0.512 | | 0.418 | |

*Notes: Regressions also include the share of household member in gender specific age groups. Standard errors in parentheses are corrected for clustering at Kebele level. *** p<0.01, ** p<0.05, * p<0.1*

***Table 5.9***
*Regressions of the standard deviation of log expected medical expenditure*

| | *(1)* | | *(2)* | | *(3)* | |
|---|---|---|---|---|---|---|
| | ***LAD*** | | ***OLS*** | | ***2SLS*** | |
| Ln(outpatient expense) t | -0.00122 | (0.00304) | -0.00149 | (0.00317) | -0.00723 | (0.0166) |
| Ln(outpatient expense) t-1 | -0.00197 | (0.00285) | -0.000115 | (0.00245) | 0.000435 | (0.0107) |
| Ln(inpatient expense) t | 0.0110 | (0.00845) | 0.00780 | (0.00600) | 0.00870 | (0.00620) |
| Ln(inpatient expense) t-1 | -0.00889 | (0.00734) | -1.97e-05 | (0.00743) | 0.000283 | (0.00764) |
| Someone in household experienced: | | | | | | |
| Illness > 30 days | -0.0286 | (0.0219) | -0.0153 | (0.0206) | -0.00920 | (0.0262) |
| Sensory impairment | -0.00785 | (0.0168) | -0.00909 | (0.0148) | -0.00811 | (0.0147) |
| Paralysis/ mobility problem | 0.00609 | (0.0197) | 0.0198 | (0.0168) | 0.0203 | (0.0168) |
| Poor/very poor health | -0.00484 | (0.0187) | 0.00275 | (0.0202) | 0.00811 | (0.0245) |
| Death in last year | -0.0629 | (0.0434) | -0.0501* | (0.0291) | -0.0517* | (0.0294) |
| 2nd poorest assets quintile group | 0.0240 | (0.0160) | 0.0139 | (0.0159) | 0.0146 | (0.0161) |
| Assets quintile 3 | 0.0456** | (0.0195) | 0.0359* | (0.0186) | 0.0365* | (0.0187) |
| Assets quintile 4 | 0.0549*** | (0.0187) | 0.0617*** | (0.0194) | 0.0626*** | (0.0195) |
| Richest assets quintile group | 0.0768*** | (0.0247) | 0.0688*** | (0.0215) | 0.0700*** | (0.0223) |
| Covered by safety net programme | 0.0342* | (0.0185) | 0.0276** | (0.0134) | 0.0277** | (0.0132) |
| Has bank account | 0.0106 | (0.0200) | 0.00268 | (0.0160) | 0.00345 | (0.0156) |
| Non-agricultural employment | -0.00408 | (0.0396) | 0.0132 | (0.0306) | 0.0154 | (0.0308) |
| Educated head | -0.00255 | (0.0110) | 0.00902 | (0.0102) | 0.00856 | (0.0104) |
| CBHI enrolled | -0.0169 | (0.0162) | -0.00756 | (0.0129) | -0.00940 | (0.0141) |
| Forgone care when sick | 0.0191 | (0.0328) | 0.0151 | (0.0323) | 0.0123 | (0.0321) |
| Minutes to nearest health center | -0.000158 | (0.00016) | 0.000108 | (0.00016) | 0.000109 | (0.000156) |
| Shock | -0.00414 | (0.0126) | 0.00530 | (0.0124) | 0.00550 | (0.0125) |
| Ln(household size) | -0.0385* | (0.0204) | -0.0274 | (0.0187) | -0.0255 | (0.0189) |
| Year 2013 | -0.000993 | (0.0128) | 0.00685 | (0.0154) | 0.00632 | (0.0158) |
| Constant | 0.337*** | (0.0480) | 0.289*** | (0.0405) | 0.284*** | (0.0422) |
| Observations | 2,631 | | 2,631 | | 2,631 | |
| R-squared | 0.070 | | 0.099 | | | |
| F-test (P-value) for joint significance: | | | | | | |
| All variables | 0.000 | | 0.000 | | 0.000 | |
| Health variables | 0.304 | | 0.336 | | 0.297 | |
| Age-sex composition | 0.453 | | 0.790 | | 0.765 | |

*Notes: Regressions also include the share of household member in gender specific age groups and district dummies. Standard errors in parentheses. Corrected for clustering at Kebele level for OLS and 2SLS. Bootstrap standard errors with 200 repetitions for LAD. *** p<0.01, ** p<0.05, * p<0.1*

## 5.6 Predictive value of expectations

We confirmed in section 5.4 that a household's expectation of medical spending for 2013 is positively correlated with the expenditure that it does incur in that year (Table 5.5, 1st column, 4th row). The analysis conducted in the previous section showed a good deal of systematic variation in the mean of expected medical expenditure with factors presumed relevant to future spending on medical care. But seventy percent of the variability in the mean of expectations remained unexplained. We now consider whether this unexplained variation in expectations is useful in predicting realized spending. If so, this would suggest that respondents hold information over and above that contained in covariates commonly available in surveys that enable them to form expectations that are somewhat accurate in predicting future medical expenses. And furthermore, that this private information is incorporated in reported subjective probabilities.

We employ a Generalised Linear Model (GLM) in which realized total medical expenditure is specified as an exponential function of covariates and estimate this by gamma Pseudo Maximum Likelihood (GPML) (Gourieroux et al 1984; Manning and Mullahy 2001; Santos Silva and Tenreyro 2006). This is a commonly used estimator for medical expenditures (Jones 2011) and offers two main advantages in the present context. First, the estimator gives less weight to observations with a large conditional mean, which increases robustness to outliers that could arise from the potential measurement error in spending on outpatient care. Second, with a very large number of observations reporting no medical expenditure, substantial inconsistency could arise from adding an arbitrary constant to these zero values before taking logs and estimating in least squares (Santos Silva and Tenreyro 2006). GPML avoids this by taking the log of the conditional expectation and performs well even with a very large proportion of zero values in the sample (Santos Silva and Tenreyro 2011).

Modeling total medical expenditure in 2013 as a function of the mean of log expected expenditure gives a significant GPML coefficient of 0.228 (SE=0.115).[34] This is consistent with the significant correlation coefficient given in Table 5.5 and implies that a one percent increase in the mean of expected expenditure is associated with an approximate increase of 0.23 percent in the spending that does actually materialize. So, expectations do have some predictive accuracy. Do they also have predictive value in addition to the forecast that can be made on the basis of observable covariates?

The first column of Table 5.10 gives GPML estimates from a model that includes the 2012 values (and the 2011 value of total expenditure) of the same covariates used to predict the mean of expected medical expenditure in Table 5.6. Lagged values of the covariates are used since, in a subsequent step, the objective is to test whether expectations add further predictive power after conditioning on observable information available to be incorporated into the expectations. Both lags of past expenditure are positively and significantly associated with actual expenditure in 2013. So, the serial correlation in log expenditures shown in Table 5.4 remains after controlling for covariates. Medical expenditure is also significantly associated with past health and it is substantially greater for households that were both the poorest and the richest according to the assets index in 2012. This may reflect a higher (unmeasured) disease burden among the poorest and greater ability to pay of the richest. Strong dependence on ability to pay is also reflected in the estimate of 86 percent lower spending by those who report forgoing health care in the past due to economic reasons.[35] A standard deviation increase in travel time (=45 minutes) to the nearest health center is associated with a one-fifth increase in expenditure.[36] This is presumably due to the cost of transport that is included in the measure of medical spending.

In the second column of Table 5.10, we add the mean of log expected expenditure. Realized expenditure is positively related to the expectation. The point estimate suggests that a one percent increase in the mean of expectation is associated with a 0.08 percent increase in actual expenditure. This coefficient is not significant using a z-test but a likelihood ratio test rejects the model that excludes the expectation (LR=4.2, p-value=0.0404). Further, in an alternative specification that uses the mean of expected expenditure, rather than the mean of the log, the expectation variable is significant (10%) even using an z-test.[37]

The coefficients on the other covariates are generally robust to adding the expectations variable, while the coefficient on the latter falls by around two-thirds when covariates are added (from 0.228 in a bivariate model to 0.0799). Hence, most of the predictive value of expected expenditure comes from processing information available in observable covariates. But respondents appear to have some residual information relevant to their future medical expenditure that they draw on in answering the subjective probability questions.

***Table 5.10***
*Estimates of Generalised Linear Model of realized total medical expenditure in 2013 (Yt+1)*

| | *without expectations* | | *with expectations* | |
|---|---|---|---|---|
| Et[lnYt+1] | | | 0.0799 | (0.113) |
| ln Yt | 0.119*** | (0.0390) | 0.117*** | (0.0393) |
| ln Yt-1 | 0.0622* | (0.0333) | 0.0604* | (0.0325) |
| Someone in the household experienced: | | | | |
| Illness > 30 days | 1.029*** | (0.343) | 1.033*** | (0.343) |
| Sensory impairment | 0.0293 | (0.273) | 0.0501 | (0.273) |
| Paralysis/ mobility problem | 0.144 | (0.280) | 0.127 | (0.279) |
| Poor/very poor health | -0.342 | (0.349) | -0.354 | (0.348) |
| Death in last year | -0.867** | (0.365) | -0.875** | (0.362) |
| 2nd poorest assets quintile group | -0.584** | (0.297) | -0.615** | (0.293) |
| Assets quintile 3 | -0.536* | (0.302) | -0.583** | (0.296) |
| Assets quintile 4 | -0.653** | (0.312) | -0.699** | (0.318) |
| Richest assets quintile group | 0.481 | (0.352) | 0.398 | (0.357) |
| Covered by safety net programme | -0.0461 | (0.380) | -0.0365 | (0.382) |
| Has bank account | -0.00318 | (0.261) | 0.0416 | (0.272) |
| Non-agricultural employment | -0.0949 | (0.627) | -0.112 | (0.621) |
| Educated head | -0.141 | (0.232) | -0.144 | (0.231) |
| CBHI enrolled | 0.109 | (0.252) | 0.0884 | (0.255) |
| Forgone care when sick | -1.995*** | (0.586) | -2.005*** | (0.589) |
| Minutes to nearest health center | 0.00434** | (0.00211) | 0.00438** | (0.00210) |
| Shock | 0.205 | (0.186) | 0.186 | (0.187) |
| Ln(household size) | 0.685* | (0.359) | 0.702* | (0.359) |
| Constant | 2.612*** | (0.947) | 2.235** | (1.120) |
| Wald test of joint significance (p-values): | | | | |
| Health variables | 0.004 | | 0.004 | |
| District dummies | 0.000 | | 0.000 | |
| Age-sex composition | 0.000 | | 0.000 | |
| Log-likelihood | -8497.9 | | -8495.8 | |
| Observations | 1,330 | | 1,330 | |

***Notes:*** *Table gives GPML estimates of total realized medical expenditure in 2013 (t+1) as an exponential function of covariates. Et[lnYt+1] is the mean expectation at time t of log expenditure in t+1. All covariates are 2012 values with the addition of the 2011 value of total realized medical expenditure. Models also include the share of household member in gender specific age groups and district dummies. Standard errors in parentheses are corrected for clustering at Kebele level. *** p<0.01, ** p<0.05, * p<0.1*

## 5.7 Do expectations influence the decision to insure?

Reported expectations are related to past medical expenditures and they are positively correlated with realized expenditures. If indeed respondents are able to use available information to anticipate, to some extent, their future medical expenses, then one might suppose that the information incorporated in the reported expectations will be utilised in decisions, such as that of whether to take out health insurance. The regressions presented in Tables 5.6 and 5.8 show that the mean of expected medical expenditure is positively, but not significantly, associated with enrolment in the CBHI scheme. Even if one overlooks the lack of significance, it is not clear what to make of the fact that households with insurance report higher expected medical expenses.[38] Coverage would be expected to reduce OOP payments, although the scheme has been found to have no significant impact on households' medical spending while raising utilization of health services (Mebratie et al 2013b). The positive correlation may therefore reflect selection – households with greater expected payments are more likely to be enrolled.[39] But testing this hypothesis requires examination of whether expectations subsequently influence the decision to enrol.

To do this, we restrict attention to districts in which the CBHI scheme was offered and to households within those districts that had not yet taken the opportunity to enrol by the time of the 2012 survey. For these households, we examine the relationship between the distribution of expected medical expenditures for the year ahead stated in 2012 and the propensity to take out coverage over the next year. Given the insurance premium does not depend on individual risk, those who report a higher expectation in 2012 have a greater incentive to enrol by 2013. Besides adverse selection on expected expenses, insurance is presumed to be motivated by its potential to reduce the variability of expenses. If households hold information on the degree of dispersion in their future medical expenses that they are able to express in the subjective probability questions and they do indeed seek to reduce this risk exposure, then, for a given degree of risk aversion, those who report a higher standard deviation of expected medical expenditure in 2012 will be more likely to have enrolled by 2013.

In Table 5.11 we split households that were not enrolled in the CBHI scheme in 2012 according to enrolment status in 2013. One quarter of households enrolled between the two surveys. For each group, we show in the top panel the sample means of the mean and standard deviation of expectations of the one-year-ahead medical expenditure stated in 2012. Contrary to the hypotheses that enrolment is motivated by adverse selection and risk exposure, there is no difference in either the means or standard deviations by insurance status.[40] The bottom panel gives the parameters of the distributions of expected expenditure reported in 2013. Those who enrolled between 2012 and 2013 reported subjective probabilities that imply a 38 percent higher mean and 31 percent higher standard deviation of expected expenditure than those who choose to remain without insurance. This is puzzling since coverage would be expected to reduce both the expectation and the dispersion of the distribution. It may be that changed circumstances, such as the onset of some health problem, caused households to revise their expectations upward and to insure. We turn to multivariate analysis to explore further whether enrolment is influenced by expectations.

***Table 5.11***
*Sample means of the mean and standard deviation of expected medical expenditure by 2013 insurance status for households not enrolled in 2012*

| | *Insurance status in 2013* | | *p-value of test equality of means* |
|---|---|---|---|
| | *Enrolled* | *Not enrolled* | |
| *Expectations reported in 2012* | | | |
| Mean | 404 | 376 | 0.488 |
| Standard deviation | 154 | 153 | 0.958 |
| *Expectations reported in 2013* | | | |
| Mean | 632 | 462 | 0.013 |
| Standard deviation | 247 | 169 | 0.020 |
| No. of observations | 127 | 353 | |

*Notes: Sample restricted to districts in which CBHI is offered and to households who had not enrolled by 2012. Only households who gave logical responses in both years are reported. The pattern of results for each year is robust to using all available responses in each year.*

The first column of Table 5.12 gives probit (marginal effects) estimates of the probability of enrolling in the CBHI scheme by 2013 for those not enrolled in 2012 as a function of the mean and standard deviation of (log) expected medical expenditures reported in 2012 and socio-demographic controls also measured in 2012. Past medical expenditure and health variables are excluded since these may provide information that is incorporated into expectations of future expenses that subsequently influence insurance enrolment.[41] Neither of the marginal effects of the two expectation variables is significantly different from zero.[42] Households in higher wealth quintiles are more likely to insure. Enrolment is positively associated with an indicator of the quality of care in the closest health facility.[43]

Ability to pay appears to be a strong constraint on enrolment. Given this, it could be that households form plans to enrol based on expectations of medical expenses that they are not able to realise. To examine this hypothesis, we model the reported intention to enrol as a function of expectations and covariates. The sample is restricted to households that were not enrolled in 2012 and/or 2013 that were asked if they planned to enrol. Probit model (marginal effects) estimates are presented in the right-hand column of Table 5.12. While the coefficient of the mean of expected expenditure is not significantly different from zero, the standard deviation of expected expenditure is positive and statistically significant.[44, 45, 46] A standard deviation increase in the latter variable is associated with an increase of 0.08 in the probability of reporting an intention to enrol. This is consistent with perceived high volatility of medical expenses motivating plans to insure, even if these plans are not ultimately implemented. Failure to fulfil plans may, but need not necessarily, represent time-inconsistency (Giné et al. 2014, Halevy 2015).[47]

All in all, despite the fact that expectations do appear to be formed on the basis of relevant information, including past medical expenses, and are to a limited extent predictive of future expenses, there is no strong evidence that these expectations are used in decision making, at least with respect to health insurance enrolment. Greater perceived risk of medical expenses may raise the willingness to insure, if not actual enrolment.

***Table 5.12***
*Probit estimates of actual and planned enrolment in CBHI scheme for households not initially enrolled*

| | ***Actually enrolled by 2013*** | | ***Plan to enrol*** | |
|---|---|---|---|---|
| Mean log expected medical exp. | 0.0254 | (0.0235) | -0.00761 | (0.0193) |
| Standard deviation log expected medical exp. | -0.127 | (0.0777) | 0.323*** | (0.0854) |
| 2nd poorest assets quintile group | 0.0789 | (0.0713) | 0.135*** | (0.0470) |
| Assets quintile 3 | 0.165** | (0.0715) | 0.168*** | (0.0531) |
| Assets quintile 4 | 0.153** | (0.0770) | 0.162** | (0.0638) |
| Richest assets quintile group | 0.159* | (0.0814) | 0.0860 | (0.0701) |
| Covered by safety net programme | 0.0637 | (0.0582) | 0.0286 | (0.0542) |
| Has bank account | 0.0892 | (0.0738) | -0.0847 | (0.0625) |
| Educated head | 0.0386 | (0.0347) | -0.00759 | (0.0351) |
| Head of hhold holds official position | 0.00144 | (0.0486) | 0.0657* | (0.0392) |
| Forgone care when sick | -0.0358 | (0.109) | 0.0738 | (0.0858) |
| Minutes to nearest health center | 0.000290 | (0.000443) | -0.000269 | (0.000452) |
| Quality of care at nearest health center | 0.142*** | (0.0542) | -0.100 | (0.0663) |
| Ln(household size) | 0.00252 | (0.0519) | 0.220*** | (0.0598) |
| Muslim | 0.0335 | (0.0761) | -0.159** | (0.0626) |
| Tigray region | 0.297*** | (0.113) | 0.223** | (0.0943) |
| Amhara region | 0.220** | (0.104) | 0.0288 | (0.102) |
| Oromiya region | 0.0619 | (0.0985) | 0.288*** | (0.0908) |
| Year dummy | | | -0.0304 | (0.0393) |
| Observations | 592 | | 1,068 | |
| Pseudo R2 | 0.113 | | 0.108 | |

*Notes: The table shows probit marginal effects. The sample for the left-hand column includes all households that were not enrolled in 2012. The dependent variable is an indicator of whether the household had enrolled by 2013. The sample for the right-hand column includes all households that were not enrolled in 2012 and/or 2013. The respective dependent variable is an indicator of whether the respondent reported that the household planned to enrol. The models also include the share of household members in gender specific age groups. Standard errors in parentheses are corrected for clustering at Kebele level. *** p<0.01, ** p<0.05, * p<0.1*

## 5.8 Conclusion

Our unique elicitation of subjective probabilities of medical expenditures reveals that the majority of rural Ethiopians are able to provide logically consistent responses, in the sense of satisfying monotonicity, that correlate with past expenses and predict future spending. This positive finding echoes that of other exercises in the elicitation of probabilistic expectations of various outcomes conducted in developing countries (Attanasio 2009; Delavande et al. 2011; Delavande, 2014). It suggests that measurement of distributions of expected expenditure offers a feasible alternative to reliance on the cross-sectional variance of realized medical expenses that, even after conditioning on covariates, is likely to substantially overstate the risk faced by any one household. But households do make mistakes in assessing their risk exposure. We find that the strength of the relationship between expected and past medical spending exceeds the degree of persistence in actual expenditure. Previously high spending households may therefore overestimate the extent to which they will gain from insurance. If these households were to respond to this misperception, then the selection would not be as adverse as would be presumed on the basis of the correlation between enrolment and past expenses. This is not to say that there is no scope for adverse selection. To a limited extent, expected expenditure predicts realized spending even after conditioning on covariates. But we find no evidence that households act on this private information. Expectations do not appear to influence the decision to take out health insurance. This is somewhat at odds with the literature, although evidence of behaviour responding to health expectations captured by subjective probabilities mostly comes from one country (Malawi) and one health condition (HIV/AIDS) (Delavande and Kohler 2012; Shapira 2013; de Paula et al. 2014). The finding that plans to insure, if not actual enrolment, are positively related to the perceived dispersion of medical expenses suggests that the desire for insurance is (partly) driven by risk exposure. We can only speculate on why this motivation does not become effective demand. It could be lack of ability to pay, which does appear to be a strong determinant of insurance enrolment. Households living close to subsistence may be particularly prone to time inconsistency (Giné et al. 2014). From a distance, enrolment in health insurance to relieve stress caused due to volatile medical expenses can seem attractive. But when the time comes to pay the premium, the urgency of other needs may take precedence over a payment to cover medical care that may not even be needed.

To the best of our knowledge, this is the first study to elicit beliefs about future spending on health care. As such, it inevitably suffers from limitations that future research should take care not to repeat. First, a feature of medical expenditure data is that many households spend nothing. Our instrument did not explicitly offer zero expenditure as a possible outcome. It would probably be preferable to first ask about the probability of spending anything at all on health care, and then the probabilities of spending within categories over the range of positive amounts. Second, the instrument asked about expectations of medical expenditure over one year, while actual expenditure on ambulatory care was recorded for the past two months. This inconsistency, which hampers comparison of the levels of expected and realized expenditure but is less of an impediment to correlation analysis, is not easy to resolve since extension of the recall period for ambulatory care is likely to increase measurement error. Nonetheless, consistency of the time span should be pursued. Third, the finding that expectations do not appear to influence the decision to insure may partly be due to the fact that two-fifths of households offered insurance had already enrolled by the time the first expectations data were collected. The remaining three-fifths do not appear to base their enrolment decision on expectations of medical spending captured by the subjective probability questions. It would obviously be preferable in future tests for selection to collect expectation data from the time at which insurance is first offered. Notwithstanding these limitations, we believe the findings from this study are sufficiently encouraging to warrant further research into how expectations of medical expenditures are formed and utilized in a number of contexts.

## Notes

[1] The paper is co-authored with Owen O'Donnell, Anagaw Mebratie, Getnet Alemu, and Arjun S. Bedi.

[2] Our results also suggest that much of the predictive power of expectations comes from observable characteristics.

[3] The premium ranges from 10 Birr (US$ 0.6) to 15 Birr per household per month. In one region (Amhara), the premium varies with household size (3 Birr per individual per month but all individuals in the household must still be enrolled). The central government subsidizes a quarter of the premium while district and regional governments are expected to cover the costs of providing a fee waiver to the poorest 10 percent of the population.

[4] Enumerators were instructed to compute the three cut offs as: A=*min*+X, B=A+X, C=B+X, where X=(*max-min*)/4.

[5] That is, the Productive Safety Net Programme (PSNP). The programme operates in food insecure districts and targets food insecure households in such districts.

[6] Refinement of the wording of the preliminary questions may be called for when this happens.

[7] For 37 (in 2012) and 24 (2013) households, information on whether they were prompted to revise their responses is missing.

[8] After prompting for revisions, the incidence of illogical responses dropped to 5 percent in Dominitz and Manski (1997). Since a principal aim of the current study is to examine the ability of low educated individuals to report subjective probabilities, we decided not to allow revision, except with respect to the reported minimum and maximum values.

[9] An additional potential explanation is that the current study did not coach respondents in the provision of subjective probabilities using a practice question, while the Indian study did so using the probability of rain the day following the interview.

[10] All the intervals are not equally spaced for the households in which the enumerators made errors in calculating the thresholds (see Table 5.2). The equivalent figure based on the 2013 data is similar with a slightly smaller peak in the first interval (see Appendix Figure A5.1).

[11] The median reported probabilities are very close to and follow the same general pattern across the intervals as the means. Specifically, the medians in 2012 (2013) respectively are: Min-A – 50 (40), A-B – 20 (20), B-C – 10 (10) and C-Max – 20 (20).

[12] From only three subjective probabilities it is not possible to establish which type of distribution fits the data best (Attanasio and Augsburg, 2012).

[13] Covariates (see Appendix Table A5.3) include household size and demographics, the head of household's education and occupation, measures of economic status, dummies for household level chronic health problems, paralysis, self-assessed health status, difficulty in hearing or speaking and a death in the household in the previous year and 96 village dummies.

[14] The small difference in the two sample means is due to missing values of some of the covariates included in the regression model.

[15] In 2012, only 3 respondents (of the 1599) stated a minimum health expenditure of zero. Admittedly, this may reflect a deficiency in the question, which did not emphasise that zero expenditure was a permitted response.

[16] For example, van Vliet (1992) finds a correlation coefficient that ranges from 0.21 to 0.27 for total health care costs in consecutive years in the Netherlands. Newhouse et al. (1989) also find a correlation coefficient that ranges from 0.09 to 0.26. French and Jones (2004) find higher persistence in health expenditures of older persons in the US and Feenberg and Skinner (1994) find high persistence in larger health expenditures in the US.

[17] Switching insurance status between periods may affect the correlation coefficient if enrolment reduces health payments of the insured. Computing the correlations by spliting the sample in to those who remained uninsured in consecutive periods and those who get insurance in the second period confirm this for total health expenditure in 2012-2013 (0.034 vs -0.024) but not in 2011-

2012 (0.037 vs 0.038). The difference is, however, not statistically significant for both pairs of years.

[18] For the correlations reported in Table 5.4, total expenditure is computed by simple extrapolation as described earlier. If, instead, we compute total expenditure as the sum of outpatient spending in the last two months and inpatient spending for the last year, the correlations decline and are significant only in logs.

[19] Restricting the sample to households with positive expenditure in consecutive years raises the correlation (without reaching significance) for total and outpatient expenditure for 2011-12 but only for outpatient expenditure for 2012-13.

[20] For example, van Vliet (1992) finds a correlation coefficient that ranges from 0.21 to 0.27 for total health care costs in consecutive years in the Netherlands. Newhouse et al. (1989) also find a correlation coefficient that ranges from 0.09 to 0.26. French and Jones (2004) find higher persistence in health expenditures of older persons in the US and Feenberg and Skinner (1994) find high persistence in larger health expenditures in the US.

[21] Switching insurance status between periods may affect the correlation coefficient if enrolment reduces health payments of the insured. Computing the correlations by spliting the sample in to those who remained uninsured in consecutive periods and those who get insurance in the second period confirm this for total health expenditure in 2012-2013 (0.034 vs -0.024) but not in 2011-2012 (0.037 vs 0.038). The difference is, however, not statistically significant for both pairs of years.

[22] For the correlations reported in Table 5.4, total expenditure is computed by simple extrapolation as described earlier. If, instead, we compute total expenditure as the sum of outpatient spending in the last two months and inpatient spending for the last year, the correlations decline and are significant only in logs.

[23] Restricting the sample to households with positive expenditure in consecutive years raises the correlation (without reaching significance) for total and outpatient expenditure for 2011-12 but only for outpatient expenditure for 2012-13.

[24] Restricting attention to the sample of households who reported chronic illness in both periods raises the correlation coefficient of total medical expenditure sub-

stantially to 0.062 for 2011-2012 and 0.097 for 2012-2013, although neither reaches significance. The correlation also rises, particularly for 2011-2012 if we exclude households that experience death of a household member between the two consecutive years.

[25] In the table, we show correlations with realized total expenditure computed by the simple extrapolation method (i.e. outpatient*6+inpatient). If instead with simply add two-monthly outpatient expenditure to inpatient expenditure, the correlations generally decline somewhat in magnitude but maintain significance.

[26] The analysis is intended to be descriptive with the purpose of assessing whether the subjective probabilities reported are sufficiently correlated with factors one would anticipate may be utilised in the formation of expectations such that there are grounds to interpret the data as expectations. Testing a specific model of expectations formation would be difficult with the data available given the distinction between inpatient and outpatient in the realized, but not the expected, expenditures, and the two month reference period for outpatient expenditure.

[27] OLS estimates based on the 2012 and 2013 observations separately show similar patterns although some estimates are no longer statistically significant in one of the two periods (See Appendix Table A5.4).

[28] A one percent increase in outpatient expenses in the last two months is likely to imply a less than one percent increase in annual expenditure assuming that the increase in not repeated in every other two monthly period throughout the year.

[29] The safety net programme is significant in the LAD regression.

[30] If the health variables are excluded from the OLS regression, then the coefficients on the past expenditure variables increase (results available on request). This is further indication that both sets of variables are capturing the extent to which expectations are formed on the basis of health-related information.

[31] Estimates are similar if we employ the mid-point of the logs of the reported minimum and maximum expected expenditure instead.

[32] The increase in expectations with wealth is slightly stronger. Expectations increase significantly with household size and the incidence of negative shocks.

[33] Estimates in first differences are provided in Appendix Table A5.6.

[34] Total realized expenditure is computed as outpatient expenditure in the last two months multiplied by six, plus inpatient expenditure in the last year. If we instead use total realized expenditure computed by simply adding the outpatient expenditure in the last two months with the inpatient expenditure in the last year, we find a significant GPML coefficient of 0.261 (SE=0.133). Coefficients in Table 5.10 generally increase in magnitude and are robust in terms of significance when this alternative calculation of total realized expenditure is used.

[35] exp(-1.995)-1=-0.864.

[36] (exp(0.00454)-1)×45=0.1957.

[37] In the alternative specification, we also enter the lagged realized expenditures in levels rather than logs. As a further robustness check, we estimated by Poisson pseudo maximum likelihood, which weights all observations equally and so may be more sensitive to outliers, rather than GPML. In this case, the mean of expected expenditure is significant at 1%. Results from these alternative specifications and estimators are available on request.

[38] The CBHI scheme operates by issuing a card that entitles the holder to free care at contracted facilities. There is no payment and subsequent reimbursement. Hence, if a household takes its coverage into account in reporting expected expenditure, it is likely to be reporting OOP payments and not the gross value of the health care anticipated to be accessed through insurance.

[39] Since there are no copayments under the scheme, moral hazard (with a high price elasticity) would not result in increased payments unless increased access to low levels of treatment resulted in referral to higher levels of treatment with associated expenditures. But even if there were such an effect, anticipation of it would require very sophisticated agents, which villagers experiencing the first two years of operation of a health insurance scheme are unlikely to be.

[40] The expectations of medical expenditure reported in 2012 could possibly take into account plans to enrol in the CBHI scheme in the coming year and the consequences this would have for OOP payments. To take account of this possibility, we have restricted the sample further to households not enrolled in 2012 and who declare at that point that they have no plans to enrol. This does not change the conclusion of there being no significant difference in expectations between those who do and not subsequently enrol in either the bivariate analysis in Table 5.11 or the multivariate analysis reported in Table 5.12.

[41] In fact, including lagged realized medical expenditure and health indicators has little or no influence on the magnitude and significance of the coefficients on the expectations variables.

[42] The mean and standard deviation of expected expenditure are highly correlated ($\varrho$=0.788), which might be considered an explanation for neither being individually significant. When the model is re-estimated first including only the mean (and covariates) and then only the standard deviation, neither is significant.

[43] The perceived quality of care is reported by the head of the nearest health facility. The specific question is: "Do you think this health center is providing the expected standard of health care services?" This was asked in a survey of 48 health centers (3 from each of the 16 districts) conducted in April-May 2011. Households were matched to health centers by proximity based on information collected from district health offices (Mebratie et al. 2015).

[44] A simple test of differences in sample means of the mean and standard deviation of expected spending between those who plan to enrol and those who do not shows no significant difference in the expected mean (ETB 437 vs ETB 412) but significantly higher expected standard deviation for those planning to enrol (ETB 177 vs ETB 141).

[45] Estimates based on the 2012 and 2013 observations (not enrolled) separately are reported in Appendix Table A5.7. In both years, the expected mean and standard deviation coefficients are positive, and the latter is always statistically significant.

[46] Household size and whether or not the head of the household ever held an official position are also associated with plans to enroll. The explanation for the former is that premia is by and large set at the household level. The latter could

be because holding an official position could relate to one's awareness about the scheme. While these results didn't come out for actual enrolment in the sub-sample analysed here, Mebratie et al. 2015 found similar results for actual enrolment in 2012.

[47] Of the households not enrolled in 2012, 59% (354/604) report that they plan to enrol in the CBHI scheme. Of those households, only 26% (91/354) had actually enrolled by 2013. Both the mean and standard deviation of expected expenditure reported in 2012 are slightly higher for those who do realise their plan to enrol (mean: 414 vs 381, standard deviation: 164 vs 153) but neither difference is significant.

# 6 A Perverse 'Net' Effect? Health Insurance and Ex-ante Moral Hazard in Ghana[1]


## Abstract

Incentive problems in insurance markets are well-established in economic theory. One of these incentive problems is related to reduced prevention efforts following insurance coverage (ex-ante moral hazard). This prediction is yet to be tested empirically with regard to health insurance, as the health domain is often considered relatively immune to perverse incentives, despite its validation in other insurance markets that entail adverse shocks. This paper tests for the presence of ex-ante moral hazard with reference to malaria prevention in Ghana. We investigate whether enrolment in the country's National Health Insurance Scheme (NHIS) negatively affects ownership and use of insecticide-treated bed nets (ITNs). We use a panel of 400 households in the Brong Ahafo region for this purpose and employ a propensity-adjusted household fixed effects model. Our results suggest that ex-ante moral hazard is present, especially when the level of effort and cost required for prevention is high. Implications of perverse incentive effects for the NHIS are briefly outlined.


## 6.1 Introduction

> "We have mosquito nets but we don't use them. If you are insured it is easier to go to the hospital [in case of malaria] [..] Why would you spend GH¢8 on the bed net while you can take GH¢2 to go to the hospital?"

This attitude expressed during a community meeting on health care utilization in the small village of Obenkrom in Central Ghana signals a potential incentive problem related to health insurance. The possibility that preventive efforts are scaled back in response to insurance coverage is known in the insurance literature as ex-ante moral hazard, to be distinguished from ex-post moral hazard, which refers to increased demand for medical care once insured (Zweifel & Manning, 2000). While the health economics literature has mostly focused on the latter (Bhattacharya & Packalen, 2008), we take prime interest in the ex-ante type of moral hazard and test for its presence in the case of malaria prevention, more specifically the use of insecticide-treated bed nets (ITNs) to protect against malaria-infested mosquitoes. We investigate whether insurance gives rise to perverse incentives for prevention by analyzing panel data collected among 400 households in central Ghana where malaria is endemic.

According to the World Health Organization, there is little evidence that Ghana managed to reduce malaria prevalence between 2000 and 2009 (WHO, 2010). It is still the country's leading cause of morbidity and mortality, accounting for an estimated 38 percent of all outpatient visits and 36 percent of all admissions into healthcare facilities. Its impact in terms of mortality is most dramatic among children under five. The 2008 Demographic and Health Survey (DHS) revealed that malaria accounted for 43 percent of all deaths in children aged 29 days to 5 years and that roughly half these deaths occurred at home (PMI, 2010). Apart from a high disease burden, malaria also typically puts a heavy financial burden on affected households. Akazili et al. (2007) estimate for a district in northern Ghana that the total cost of a malaria episode equals US$6.39, which is made up of US$1.87 in direct out-of-pocket expenditure on treatment, and US$4.52 in foregone earnings due to working days lost. On an annual basis, the authors calculate that the cost of malaria amounts to 34 percent of the income of a poor household (living on less than a dollar a day).

Households can avoid the direct cost of malaria treatment by enrolling in Ghana's National Health Insurance Scheme (NHIS), which was launched in 2003 to provide Ghanaians with financial protection against negative health shocks. The scheme's benefit package covers about 95 per cent of the country's common health problems including malaria. Participation in NHIS, which is implemented at the district level, requires households to pay an annual premium that is progressive with income (as well as an annual processing fee of about GH¢4). The minimum premium, which applies to informal sector workers, is GH¢7.2 (PPP$12.4) per annum, while the maximum premium currently stands at GH¢48 (PPP$82.6). The "core poor" (indigents) are exempted from premium payments as well as minors (under 18) and the elderly (over 70). These waivers are partly funded by public sector employees, who tend to be levied a 2.5% social security contribution earmarked for NHIS. In return, these contributors are exempted from premium payment if they register for the scheme.

However, insurance neither eliminates the disease burden from malaria (disutility of being sick) nor the indirect cost from foregone earnings, which requires an effective prevention strategy instead. The most prominent of these in malaria endemic regions is sleeping under an insecticide-treated bed net (ITN), the effectiveness of which is corroborated in a number of studies. Estimates of reductions in child mortality as a result of ITN use range from 20% to 60% (e.g. Binka et al., 1996; D'Alessandro et al., 1995; Nevill et al., 1996; Phillips-Howard et al., 2003). Besides, a high level of ITN coverage within a community reduces the overall infective mosquito population (Gimnig et al., 2003; Howard et al., 2000). Anecdotal and entomological evidence suggests that untreated nets in a relatively good condition can also protect against malaria (Guyatt & Snow, 2002). Their effectiveness notwithstanding, adoption and consistent use of bed nets is far from universal in Ghana. The 2008 DHS revealed that 45 per cent of Ghanaian households owned at least one bed net (treated or untreated) and 33 per cent owned at least one ITN. A mere 15 per cent of the population actually slept under a net the night prior to the survey, although this percentage is almost double (28 per cent) for children under five (GSS et al., 2009).

This low uptake of nets partly stems from an information problem, as studies point out that people do not always associate malaria with mosquito bites (see e.g. Agyepong & Manderson, 1999; Ahorlu et al., 1997; Hill et al., 2003). Even among bed net users it is often protection against nuisance of mosquitoes (and other insects) that motivates adoption rather than malaria avoidance per se, as witnessed in Burundi (Van Bortel et al., 1996), Guatemala (Klein et al., 1995) and rural Cameroon (Louis et al., 1992). This likely occurs in Ghana as well, where Adongo et al. (2005) report for the north of the country that nets tend to be used by adults instead of children because of the notion that adults need a good night's sleep to prepare for next day's work. The information failure also shows from the finding that bed nets are increasingly used for the intended purpose when educational efforts regarding malaria transmission are stepped up (Agyepong & Manderson, 1999). Also, health education appears to stimulate bed net use, provided that the target group has a certain minimum level of trust in health workers (De Hoop & Van Kempen, 2010).

Other problems related to ITN use are the fact that nets reduce the risk of contracting malaria but cannot eliminate it altogether -the psychological effect of which varies with one's risk attitude- and that ITN use is costly. The acquisition price of an ITN is not inconsiderable at about US$6.5 in commercial outlets, and even when distributed for free, ITN use entails 'costs' in terms of the (perceived) discomfort of sleeping under a bed net. Since insurance shifts the relative cost of prevention and treatment in favor of the latter, the question is warranted whether insurance could negatively impact on ITN adoption (both ownership and use). This hypothesized negative effect highly depends on the particularities of the health shock these actions aim to avoid, their effectiveness in doing so, the level of discomfort they entail and the degree of effort they require. In situations where preventive care itself is financed by the insurance scheme, this negative effect is likely to be small, unless the perceived discomfort of the preventive strategy and/or associated effort are excessive. In fact, Mensah et al. (2010), using cross-sectional data, have shown that NHIS in Ghana increases pre- and postnatal preventive care visits. These preventive measures, however, are in the insurance package and cannot be used to argue against ex-ante moral hazard. ITN use, which is excluded from the benefit package, nonetheless requires a different level of effort and might entail higher perceived discomfort than the preventive check-ups analyzed in Mensah et al. (2010).

To our knowledge, the interaction between insurance and malaria prevention has not yet been studied. However, we identified a small number of studies that provide insight in the impact of insurance schemes on other types of preventive health behavior in a developed country context. These studies and major reasons why ex-ante moral hazard received little attention in health insurance are outlined below.

## 6.2 Ex-ante moral hazard

A host of empirical studies have documented ex-post moral hazard in health insurance in both developed and developing country contexts (see, for example, Asenso-Okeyere, 1998; Ekman, 2004; Harmon & Nolan, 2001; Sapelli & Vial, 2003, Yip & Berman, 2001). By contrast, there is scant evidence on the existence of ex-ante moral hazard. While it tends to be cited as a possibility, it is often downplayed (Dave & Kaestner, 2009). One reason not to consider ex-ante moral hazard as a serious problem is the idea that uncompensated loss of health is consequential (Cutler & Zeckhauser, 2000). Put differently, people are assumed not to take a gamble with their personal health or that of household members, at least not to the extent they would do with material resources. Second, most health insurance schemes have incomplete coverage, reducing the moral hazard problem directly. Kenkel (2000) points out that even under full coverage there will be a utility loss due to illness and posits that individuals will factor in forgone earnings and the agony of illness in their decision.

The few empirical studies that have tested for ex-ante moral hazard, which mainly concern developed country contexts, provide mixed evidence regarding its presence (Zweifel & Manning, 2000; Kenkel, 2000). For instance, in the US the RAND Health Insurance Experiment revealed that habits like smoking, drinking and exercise are not significantly affected by less generous health insurance (Newhouse, 1993). Using US data with naturally occurring exogenous variation in health insurance, Card et al. (2008) also failed to find an association between insurance status and changes in smoking, exercise and weight. Testing for the same hypothesis in Britain, Courbage & De Coulon (2004) showed that preventive activities (smoking and exercising) are not affected by private health insurance. Trujillo et al. (2010) report a positive rather than a negative effect from insurance on prevention in a cross-sectional study among diabetes patients in Colombia.

On the other hand, a state-mandated health insurance for the treatment of diabetes, which is linked to obesity, was associated with higher bodymass index among diabetics in the US (Klick & Stratmann, 2007). Also, Dave & Kaestner (2009) found evidence that health insurance (Medicare) reduces prevention and increases unhealthy behaviors among elderly American men, i.e., when controlling for contact with medical professionals. They argue that obtaining insurance has two potentially offsetting effects on prevention. While it should reduce prevention because insurance lowers the cost of medical care (ex-ante moral hazard), increased contact with medical professionals may alter information on benefits of prevention and thereby stimulate it.

Moreover, evidence supporting substantial ex-ante moral hazard is found in other insurance markets. For instance, a more generous automobile insurance is found to have caused a significant decrease in prevention and an increase in accidents (Chiappori, 2000). Similarly, Cohen & Dehejia (2004) showed that compulsory car insurance laws are associated with increased car fatalities. More related to health shocks, an increase in insurance generosity for workers' accident compensation is found to be associated with more work place injuries (Fortin & Lanoie, 2000; Kaestner & Carroll, 1997).

The fact that empirical studies on car insurance and workers' compensation show a significant ex-ante moral hazard is puzzling. A reduced prevention effort in driving and at work would result in adverse and mostly severe health shocks, which sits awkwardly with the idea that the health domain is relatively immune to perverse incentives regarding prevention. Why then do some empirical studies fail to detect ex-ante moral hazard? The timing of the materialization of the health risks involved plays a potential role here. As Dave & Kaestner (2009) observe, the cost of inaction likely befalls individuals only in the longer run in the case of unhealthy behavior like smoking, so that the case for prevention is weak even without insurance, which attenuates a potential effect from insuring oneself. In our case, the benefits from ITN use are immediate and ex-ante moral hazard should thus manifest itself more clearly. This notwithstanding, the evidence on ex-ante moral hazard is still inconclusive and its theoretical underpinnings require more careful testing.

## 6.3 Empirical strategy

### 6.3.1 Constructing the counterfactual

Our identification strategy relies on households who change insurance status between two periods. As insurance uptake is non-random, conducting a randomized controlled experiment is not possible in our case. Our analysis of the effect of insurance on ownership and use of bed nets follows a quasi-experimental approach that aims to mimic the experimental controlled trial by matching the treated households (insured) with the untreated households (uninsured) such that the only difference between the two is just the treatment variable (NHIS participation).

More formally, we follow the potential outcome approach developed by Rubin (1974, 1978). The approach views causal effects as those that result from a comparison of potential outcomes defined on the same unit. Thus, the main challenge is to identify the counterfactual: how would a certain household have behaved if it had not taken insurance? Since this is by definition unobservable, we have to resort to a comparison with the non-insured, i.e., to compare 'treated' and 'untreated' units in impact evaluation jargon. Using the mean outcome of the untreated (non-insured) households as the counterfactual is naïve, since covariates that determine insurance uptake might also determine bed net use and ownership. If so, our estimate likely suffers from self-selection bias in a quasi-experimental set-up. In order to avoid this selection problem we have to call upon two identifying assumptions. The first is the conditional independence assumption (cf. Lechner, 2001), which implies that decisions on bed net adoption are independent of selection into insurance, given a set of observable covariates that may explain insurance status but are not themselves affected by it. This may include relatively exogenous variables such as household composition, age, education levels and household wealth (e.g. land ownership). Rosenbaum & Rubin (1983) suggest the use of a balancing score that summarizes this (potentially large) set of observable covariates into a single indicator, viz. the probability of being insured conditional on this set of variables. Thus, we first predict the probability of selection (being insured) in a probit model and subsequently match insured and uninsured households based on this so-called propensity score. However, to be able to meaningfully match insured and uninsured households, they should be sufficiently alike, i.e., have similar propensity scores. This brings out the second identifying assumption of common support; there exists an overlap in propensity scores and there is no perfect predictability of insurance status given the set of observables. Under these two conditions our propensity score matching estimator is simply the mean difference in outcomes over the common support range, which is known in the impact evaluation literature as the "average treatment effect on the treated" (ATT).

While the propensity-score matching estimator has the advantage of balancing households on observable factors along a single dimension (the estimated propensity score), it has the disadvantage that it assumes selection is solely based on observable household characteristics. Even after balancing on the propensity score a household's decision whether to be insured is not necessarily random. The insurance decision is a highly complex one and may well be correlated with, among others, unobservable health shocks, risk attitude and time preferences, all of which may at the same time be correlated with ITN use.

Studies have in fact underscored the importance of a household's risk attitude in insurance decisions. The stronger a household's aversion to risk, the higher the probability that a household takes up insurance (Monheit & Vistnes, 2008). This aversion to risk is also what is supposed to drive the adoption of ITNs. Time preference (e.g. myopia and hyperbolic discounting) is a closely related factor that affects both insurance and prevention decisions. For example, Tarozzi & Mahajan (2011) establish in a randomized controlled trial that time preferences are strongly related to ITN uptake in the Indian State of Orissa, even more so than risk and cost preferences. Another type of attitude, particularly but not exclusively relevant in Sub-Sahara Africa, concerns a household's beliefs regarding the causes of health problems and the extent to which one can control these. This boils down to whether one harbors traditional (animist) or modern views regarding ill health. In our sample we have substantial heterogeneity in this respect, as one in every five households reportedly believes that witchcraft (or another supernatural force) can cause malaria. The study by Jehu-Appiah et al. (2010) probes into such beliefs, asking respondents for example to what extent they agree with the following statement: "Health is a matter of fate (in the hands of God) and that insurance cannot help me deal with its consequences". Such beliefs are shown to be relevant in explaining NHIS enrolment, at least for certain parts of the income distribution. Hence, selection on non-observable factors cannot be ignored.

When unobserved attitudes can be assumed to remain relatively fixed over time, as is likely to be the case for risk and time preferences as well as traditional beliefs regarding ill health, bias from selection on such unobservables can be avoided by comparing treated and untreated units in a panel structure. Therefore, a household fixed effects model is employed for our major specification. Unlike the propensity-score matching estimator, this model exploits the longitudinal nature of the data to account for time-invariant household-specific unobservable factors. The propensity score matching is integrated in our fixed effects model, since we only estimate the effect of insurance on ITN adoption among the sub-sample of households that look alike according to the counterfactual constructed using the propensity score. A potential limitation of a household fixed effects model is that there might be unobservable factors that vary over time and are correlated with both the decision to become insured and to adopt ITNs. In an attempt to account for these we control for health shocks, shifts in health information, and other time-varying measures of income and socio-economic status in the form of robustness checks. Further sensitivity checks of the results are discussed in the final part of the paper.

### 6.3.2 Sample description

The study is located in Ghana's Brong Ahafo region, which features the next-to-highest NHIS penetration rate of all regions in the country: 77 percent of the population was enrolled in 2009, which compared favorably with the national average of 62 percent (NHIA, 2009). Also, ownership and use of ITNs is relatively high in Brong Ahafo compared to national standards: 46 per cent of the households owned an ITN and half of under-five children reportedly slept under an ITN in 2008 (GSS et al., 2009).

A panel was built on 400 households who were surveyed in September 2007 and re-surveyed after two years (September 2009). Seven households could not be traced in the second round and were replaced by neighboring households. All households live in the catchment area of a regional Catholic mission hospital, which commissioned the current research on the effect of insurance roll-out in their area of operation. The surveyed households are spread over eleven different communities, which were purposively sampled such that the selected communities reflect the existing variation in community size (ranging from 700 to 5,000 inhabitants) and in distance from the main road (on which the hospital is located). Seven of the villages are located in Asutifi district and four in the adjacent Asunafo district. The latter communities, from which half of our sample is drawn, are particularly distant from the regional health infrastructure (two-hour drive from main road). Community selection was done in close cooperation with hospital staff knowledgeable on the composition of the catchment area.

The number of households interviewed in a community is proportional to its population size and within communities households were randomly drawn for inclusion in the study. For the largest community (Nkaseim) a household register was available, which was used for randomization, whereas in the other communities a random walk procedure was followed in the absence of a complete household list. In June 2010 a series of participatory debriefing sessions on the outcomes of the study were organized in five of the surveyed communities. Throughout the paper we make occasional reference to information gathered in these community meetings. The research was conducted jointly with local health authorities and prior consent was obtained from traditional leaders in all communities under study.

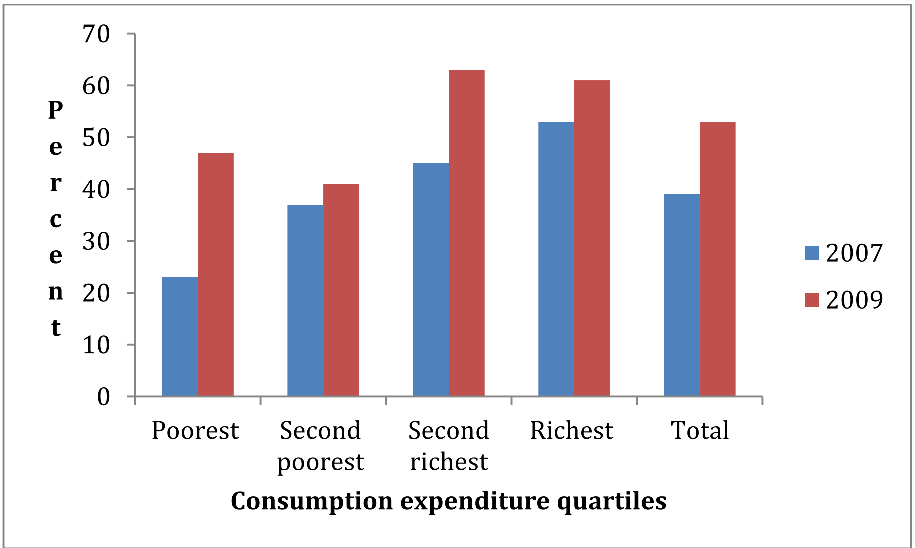
In order to define a household's insurance status, respondents who indicated to have registered for NHIS were asked to present their actual insurance card. A small number of very recent subscribers were not able to do so, given the time lag between registration and actual receipt of the card, without which healthcare providers do not consider the patient to be insured. If presented, the validity of the card was checked by the surveyor, since the insurance needs to be renewed annually and can thus be expired if no action was taken. We only consider households that could present a valid NHIS card to be insured.

Thus defined, our data show that the fraction of insured households in the sample, which stood at 39 percent in 2007, had increased to 53 percent by 2009 (Figure 6.1). This increase was concentrated among the poorest 25 per cent of households (as measured by expenditure), who doubled their participation from 23 to 47 per cent. By comparison, participation moved up from 53 to 62 per cent in the top quartile. Despite the 36 per cent overall increase in enrolment in two years, insurance penetration in our sample compares poorly with the corresponding figure for the entire Brong Ahafo region (77 per cent in 2008). Bed net ownership, on the other hand, is relatively high: 4 out of every 5 households reportedly owned at least one bed net (treated or untreated) in 2009, against roughly one in two households in the entire region.

Table 6.1 (panel A) shows that in 2007 there is no significant difference in ownership of bed nets, either measured as dummy or in per capita terms, between households who remained uninsured between 2007 and 2009 and those who gained insurance coverage between 2007 and 2009. The same holds for acquisition rates of bed nets in the period

2007-09. These results on ownership should be interpreted with caution, however, as the insured may have acquired their nets before taking insurance. Since we do not have a pure baseline (pre-NHIS data), our analysis zooms in on the difference between those who gain insurance between the two survey rounds and those who remain uninsured throughout.

***Figure 6.1***
*NHIS enrolment (per cent of households)*




When analyzing use indicators for these two groups we make a distinction between two types of nets, i.e., those that are factory-treated (referred to as 'FTN') and ordinary nets that are periodically soaked in insecticides (referred to as 'self-treated nets' (STN)), where the former are more common. Once acquired, self-treated nets entail a substantial effort and cost compared to factory-treated nets. Hence, we posit that if there is ex-ante moral hazard it should be manifested more clearly in STN than in FTN adoption. We observe similar levels of FTN use in 2007 and a negative change in its use over the two-year period for both groups. However, though not statistically significant, the decline in FTN use among those who gained insurance in this period exceeds the decline for those who remained uninsured by 75%. STN use shows a markedly different picture. Those who gained insurance started with a significantly higher use of STNs, but over the two years their use rate declines substantially, while it increases for those households who do not take up insurance. The mean difference in change is statistically significant ($p < 0.01$).

This sharp drop in bed net use among those who gained insurance relative to those who remain uninsured cannot be taken as firm evidence of ex-ante moral hazard, as initial differences in household characteristics could have brought about such a diverging trend. Panel B of Table 6.1, however, reveals minor initial differences in economic status. Among the list of measures of both permanent income and current income presented in panel B, statistically speaking, only 'the number of rooms in the house' variable shows that those who gained NHIS are less poor than those who remained uninsured. Yet, statistical insignificance need not imply that the two groups are similar ex-ante. For example, 73 per cent of households who remained uninsured live in a mud/thatch house rather than in a brick construction, which serves as a crude proxy for income poverty (cf. Sarpong et al., 2010), against only 63 per cent of those who gained insurance. The use of propensity score matching will help to avoid any such remaining systematic differences in these observable characteristics.

Those who gained insurance are not only better-off, they are also better informed about the actual cause of malaria, as confirmed in panel C. We solicited perceptions regarding potential causes (multiple answers possible) of both uncomplicated and complicated malaria, which are locally distinguished. Uncomplicated malaria is associated with fever, headache, vomiting, chills and loss of appetite, whereas malaria cases are considered complicated when, in addition to these symptoms, they involve anemia, convulsions, general lethargy and a swollen body. Only misperceptions on the causes of uncomplicated malaria are reported, as the responses are very similar for both types. Unfortunately, these data are available for 2009 only. Arguably, such perceptions are fairly static in the short run (yet, later in our analysis, we control for exposure to health education that could change these perceptions). It appears that throughout the sample, among those who gained insurance and remained uninsured alike, mosquito bites are perceived as the main transmission mechanism for malaria, but not as the unique one. Nevertheless, a significantly higher percentage of those who remain uninsured report other causes of malaria, e.g. witchcraft and drinking contaminated water, than those who gained insurance. Interestingly, both groups maintain similar perceptions regarding the effectiveness of ITNs, despite the larger degree of confusion on malaria transmission among those who remain uninsured. We also do not find notable disparities in participation rates in health education between the two groups.

As signaled by Dave & Kaestner (2009), insured households are likely to be more aware of the benefits of prevention than the uninsured via increased contact with health professionals and this may have an offsetting effect on ex-ante moral hazard. In Table 6.2 we estimate the probability of a household reporting that malaria can be caused by factors other than mosquito bites, as well as the probability that a household indicates that bed nets are effective, on whether or not a household was ever insured (either in 2007 or 2009), thereby controlling for other covariates. While for most of these variables we do not find evidence that insurance creates awareness, being insured is associated with a lower probability of perceiving witchcraft as a cause of malaria. Due to the cross-sectional nature of the data it is unclear to what extent this perceptual difference stems from increased contact of the insured with health professionals, however. Assuming that insurance helps to create awareness, our results presented in the next section should be considered as a lower bound of the true ex-ante moral hazard (as awareness due to insurance partly offsets the perverse incentive effect).

Finally, we checked the possibility that NHIS households switched from ITN use to alternative malaria prevention strategies, such as mosquito-proof window netting and clearing bushes or draining stagnant water around the house where mosquitoes breed. We also checked for use of mosquito coils and other insect repellents in the period between the two surveys. Simple non-parametric comparisons, reported in Table 6.3, do not reveal a diverging trend between those who remain uninsured and those who gained insurance for any of these strategies, except for the drainage of stagnant water around the house. While stagnant water was more frequently observed over time around the houses of those who gained insurance, the reverse trend is visible for those who remained uninsured, which is consistent with an ex-ante moral hazard argument.

***Table 6.1***
*Descriptive statistics*

| | ***Remain uninsured (mean)*** | ***Switched to be insured (mean)*** | ***p-value for difference*** |
|---|---|---|---|
| ***A. Bed net ownership and use ( in 2007 and change)*** | | | |
| Household owns ≥ 1 net (treated or untreated), 2007 | 0.714 | 0.681 | 0.582 |
| Change 2007-2009 | 0.192 | 0.161 | 0.646 |
| # of nets owned / # of household members, 2007 | 0.255 | 0.302 | 0.257 |
| Change 2007-2009 | 0.190 | 0.123 | 0.211 |
| Slept under 'factory-treated net' (FTN) (# of members in household), 2007 | 1.299 | 1.351 | 0.786 |
| Change 2007-2009 | -0.349 | -0.613 | 0.214 |
| Slept under 'self-treated net' (STN) (# of members in household), 2007 | 0.156 | 0.447 | 0.011** |
| Change 2007-2009 | 0.075 | -0.290 | 0.002*** |
| **Note:** *The 'change 2007-2009' rows correspond to the variable in the immediate preceding row* | | | |
| ***B. Economic status ( in 2007 )*** | | | |
| Mud/thatch house (vs. brick/concrete) | 0.731 | 0.638 | 0.130 |
| Number of dwelling units in the house | 4.267 | 4.543 | 0.429 |
| Number of rooms in the house | 2.151 | 2.602 | 0.046** |
| Ownership of the house (1=Yes; 0=No) | 0.667 | 0.652 | 0.819 |
| Savings by head of household | 0.295 | 0.319 | 0.687 |
| Savings by spouse | 0.145 | 0.156 | 0.841 |
| Household consumption expenditure (excl. health expenses) | 2839 | 3195 | 0.393 |
| ***C. Perceptions about causes of malaria and perceived effectiveness of bed nets (2009)*** | | | |
| Uncomplicated malaria is caused by (multiple answers possible): | | | |
| Mosquito bites | 0.952 | 0.936 | 0.575 |
| Standing in sun for too long | 0.952 | 0.936 | 0.584 |
| Drinking unclean water | 0.938 | 0.850 | 0.023** |
| Eating sweets | 0.567 | 0.528 | 0.553 |
| Witchcraft | 0.284 | 0.090 | 0.000*** |
| "Bed nets are effective in preventing uncomplicated malaria" | 0.914 | 0.856 | 0.164 |

***** and** refer to significance at 1% and 5% respectively; For effectiveness of bed nets, our instrument employs a scale variable (1=Strongly disagree, .. , 5=Strongly agree) which is then transformed to a dummy variable (agree/disagree)*

***Table 6.2***
*Effect of NHIS on perceptions*

| | ***Malaria is caused by:*** | | | | |
|---|---|---|---|---|---|
| | ***Witchcraft*** | ***Drinking unclean water*** | ***Eating sweets*** | ***Excessive exposure to sunlight*** | ***Perceived effectiveness of bed net*** |
| Insured in either 2007 or 2009 | -0.408** (0.183) | -0.189 (0.226) | -0.155 (0.161) | -0.141 (0.274) | -0.189 (0.222) |
| number of observations | 354 | 362 | 359 | 364 | 354 |
| Pseudo R-square | 0.105 | 0.129 | 0.097 | 0.248 | 0.063 |

*Notes: Reported figures are coefficients from a probit model; ** represents statistical significance at 5% level; Variables included in the model: age, age square and sex of household head, share of household members who are female, below 15 and below 5, construction material of house, number of dwelling units in the house, number of rooms, whether the household owns the house and dummies for religion, major occupation of the household head and village dummies.*

***Table 6.3***
*Alternative malaria prevention strategies*

| ***Other malaria/mosquito prevention strategies*** | ***Remained uninsured (mean)*** | ***Switched to be insured (mean)*** | ***p-value for differences in means*** |
|---|---|---|---|
| Used any repellents (mosquito coils, insect repellents) in the past 2 years (1=Yes; 0=No) | 0.403 | 0.396 | 0.913 |
| Expenditure on repellents in past two years (in GH¢) | 10.31 | 14.00 | 0.448 |
| Dwelling has mosquito-proof windows (change) | 0.096 | 0.096 | 0.998 |
| Bushes around the house (change) | 0.027 | 0.117 | 0.211 |
| Stagnant water around the house (change) | -0.014 | 0.085 | 0.076 |

## 6.4 Analysis

### 6.4.1 Matching variables: exogenous determinants of participation

The first step in our identification strategy is estimating propensity scores for the sampled households, which requires modeling NHIS participation. The propensity score matching procedure aims to allow for a comparison of bed net ownership and use between NHIS and non-NHIS households that have a similar ex-ante probability of participating in NHIS. Because the matching strategy builds on the conditional independence assumption, it is only those variables that are unaffected by insurance, or anticipation of it, that should be included in this participation model (Caliendo & Kopeinig, 2008). Moreover, we only take into account exogenous variables that have a clear theoretical link with health insurance and preventive health behavior, so as to avoid problems related to over-parameterization of the model (Augurzky & Schmidt, 2001; Bryson et al. 2002). Table 6.4 presents the variables that were included in the probit model to explain participation and their marginal effects.

First, we controlled for household demographic characteristics like age and sex of the household head, share of female members, share of members below 15 years, share of members below 5 years, and whether household size exceeds four (related to the fact that for some questions in the survey we only asked information up to four household members). These demographic characteristics might affect insurance uptake and ITN use, as they could shape risk attitudes, and as suggested by Koch & Alaba (2010), indicate health status. Age and sex of the household head may also pick up differences in education, which we cannot include as a separate variable due to missing values on this variable. However, Table 6.4 does not show a significant effect for any of the demographic factors.

Because insurance uptake and (to a lesser extent) ITN use are costly, covariates that proxy for economic status are considered. Savings, consumption and durables ownership are not included, because we reckon that their relatively liquid nature can serve to finance out-of-pocket health expenditure and thus fail the exogeneity test. We rely on more time-invariant indicators like construction material of the house, size of the house, ownership status and main occupation of the household head instead.

***Table 6.4***
*Probit model for NHIS participation*

| ***Variables*** | ***Marginal effect*** | ***Variables*** | ***Marginal effect*** |
|---|---|---|---|
| *Demographics* | | *Ethnicity of head (ref: Asante)* | |
| Age of head | 0.004 (0.009) | Akwapim | 0.046 (0.096) |
| (Age of head)2 | 0.000 (0.000) | Fanti | 0.017 (0.113) |
| Sex of head (1=male; 0=female) | 0.022(0.054) | Other Akan | -0.224**(0.097) |
| Share of female members | 0.045 (0.100) | Ga-Adangbe | -0.193 (0.112) |
| Share of members below age 15 | -0.112 (0.119) | Ewe | -0.121 (0.090) |
| Share of members below age 5 | 0.067 (0.139) | Others | -0.042 (0.064) |
| Less than 4 household members | -0.006 (0.062) | *Village (ref: Awewoho)* | |
| *Economic Status* | | Apenenadi | 0.062 (0.118) |
| Mud/thatch house (vs. brick/concrete) | -0.147*** (0.047) | Wuramumuso | 0.483*** (0.061) |
| # of dwelling units in the house | 0.017* (0.009) | Obenkrom | 0.306*** (0.097) |
| # of rooms in the house | 0.010 (0.012) | Antwigyeikrom | -0.287*** (0.082) |
| Ownership of house | 0.084* (0.048) | Amanfrom | 0.313** (0.107) |
| *Main occupation of head (ref: no occupation)* | | Ataneata | 0.083 (0.176) |
| Agricultural wage labor | -0.019 (0.174) | Mempehia | 0.433** (0.116) |
| Non-agric. wage labor | 0.355** (0.134) | Nkrankrom | 0.166 (0.103) |
| Agric. self employed | 0.071 (0.156) | Pomakrom | -0.156** (0.071) |
| Non-agri. self employed | -0.015 (0.166) | Nkaseim | 0.009 (0.089) |
| *Religion (ref: Presbyterian)* | | Observations | 761 |
| No religion | 0.031 (0.197) | Pseudo R-square | 0.184 |
| Catholic | 0.112 (0.103) | | |
| Methodist | 0.168 (0.107) | | |
| Pentecostal | 0.005 (0.097) | | |
| Spiritualist | 0.152 (0.138) | | |
| Other Christian | 0.072 (0.107) | | |
| Muslim | 0.035 (0.117) | | |
| Traditional | -0.310 **(0.108) | | |

*Standard errors in parentheses; ***, ** and * represent statistical significance at 1, 5 and 10 per cent level*

Table 6.4 corroborates that a better economic position raises the likelihood of being insured. Households living in a mud house are 14.7 per cent less likely to be insured, for example, than those living in a brick construction. Also, households headed by non-agricultural wage laborers have a higher likelihood of being insured than those with household heads in other occupational categories, which may partly be due to the strong incentive for certain groups of civil servants to register for NHIS, given their contribution to the scheme through the social security system.

Other variables used in our specification include religion, ethnicity, and a set of village dummies. These variables could proxy for socio-cultural factors, in particular the strength of traditional beliefs regarding ill health, and physical distance from modern health infrastructure. It shows that households headed by a traditional believer are 31 per cent less likely to be insured compared to the reference category (Presbyterian). Also, households in the remote village of Awewoho have a significantly lower probability to enroll in NHIS than more proximate households in Wuramumuso, Obenkrom and Amanfrom, as expected.

The matching procedure was successful in balancing the sample using the propensity scores, which range from 0.002 to 0.998. Overall, 97.6 percent of the observations whose probability is estimated turn out to be in the region of common support (~0.073, ~0.998). The balancing property test is fulfilled based on the optimal number of blocks (six) that ensure that the mean propensity score in each of the blocks is not different between insured and uninsured.

### 6.4.2 Estimation results: non- parametric and fixed effects estimations

In this section we investigate the causal effects of insurance on bed net ownership and use, for which we use the same four outcome variables as in panel A of Table 6.1. We present estimates of ATT based on 1) nearest neighbor (NN) matching algorithm with replacement, and 2) a propensity adjusted fixed effects model. We also check for the robustness of results to different econometric concerns.

Panel A in Table 6.5 shows the results for NN matching with replacement. This variant of the NN matching algorithm is chosen, because it decreases the bias by increasing the average quality of the matching. Even though this is traded off against an explosion in variance (Caliendo & Kopeinig, 2008; Dehejia & Wahba 2002), it provides the most appropriate estimator due to the fact that there are a relatively large number of insured households in the last block of propensity score compared to the uninsured. The estimates indicate a negative ATT both for sleeping under a factory-treated and self-treated net and a positive ATT for ownership variables. Bed net ownership in per capita terms has a significantly positive ATT while use of self-treated net has a significantly negative ATT. Bootstrapped standard errors are used. This non-parametric estimation indicates that bed net ownership increases with insurance, at least when measured in per capita terms, which is not in line with an ex-ante moral hazard argument. On the other hand, insurance significantly reduces the use of self-treated nets (STNs), while the result for factory- treated nets (FTNs) is not significant.

Let us now turn to our major baseline specification, which is reported in panel B of Table 6.5. Here we employ the fixed effects regression model, which controls for time-constant unobservable factors, unlike the propensity score matching estimator in panel A. The negative sign for all four outcome variables is suggestive of the prediction of ex-ante moral hazard, even if it is only sleeping under STNs that is precisely estimated. Like the non-parametric estimation, the fixed effects model indicates that in 100 insured households, around 20 people do not sleep under STNs due to insurance uptake. Health insurance apparently increases the benefit of curative care relative to preventive care, and most strongly so if the level of effort, cost and discomfort involved in prevention is higher (the case of STNs).

Notwithstanding its advantage in controlling for time-invariant unobservable factors, the fixed effects model does not, as indicated earlier, account for unobservable factors that are subject to change over relatively short time periods. For instance, health shocks or a shift in health information through health education between the two waves of the survey may drive both insurance status and the use of these prevention strategies. As a robustness check, we present a fixed effects model that additionally controls for time-variant covariates reflecting health shocks, health information, use of alternative malaria prevention strategies, and measures of income and socio-economic status. The corresponding results in panel C of Table 6.5 are fairly similar to those reported in panel B.

**Table 6.5**
*Effect of insurance on bed net ownership and use*

| | Bed net ownership (dummy) | Bed net ownership (per capita) | # of members who slept under factory-treated net (FTN) | # of members who slept under self-treated net (STN) |
|---|---|---|---|---|
| *Panel A: Non parametric: Nearest Neighbor with replacement* | | | | |
| Insurance | 0.078 | 0.081** | -0.027 | -0.244** |
| | (0.045) | (0.040) | (0.155) | (0.117) |
| No. of observations | 757 | 751 | 755 | 757 |
| *Panel B: Household fixed effects (major baseline specification)* | | | | |
| Insurance | -0.016 | -0.050 | -0.077 | -0.196** |
| | (0.049) | (0.045) | (0.138) | (0.082) |
| No. of observations | 740 | 735 | 739 | 740 |
| R-squared (within) | 0.102 | 0.157 | 0.100 | 0.030 |
| *Panel C: Robustness to time varying covariates, household fixed effects* | | | | |
| Insurance | -0.007 | -0.069 | -0.086 | -0.198** |
| | (0.055) | (0.046) | (0.161) | (0.089) |
| No. of observations | 671 | 668 | 670 | 671 |
| R-squared (within) | 0.182 | 0.276 | 0.183 | 0.103 |
| *Panel D: Robustness among sub- sample who had bed net in both rounds, household fixed effects* | | | | |
| Insurance | | | -0.069 | -0.248** |
| | | | (0.173) | (0.107) |
| No. of observations | | | 490 | 491 |
| R-squared (within) | | | 0.291 | 0.046 |
| *Panel E: Robustness: (Regressing change in outcome on change in insurance controlling for health information variables regarding causes of malaria in 2009)* | | | | |
| Insurance | -0.020 | -0.049 | -0.029 | -0.159* |
| | (0.049) | (0.041) | (0.154) | (0.088) |
| No. of observations | 322 | 320 | 322 | 322 |
| R-squared | 0.011 | 0.038 | 0.029 | 0.035 |

*Notes: ***, ** and * represent statistical significance at 1, 5 and 10 per cent level; Standard errors in parenthesis (bootstrapped standard errors for NN matching, robust standard errors for fixed effects); Number of groups in panel B(380), C(370) and D(250). In panel C, time varying covariates controlled for include i) indicators of health ( death of member of household past 2 years, at least one day lost due to poor health past month, diarrhea experience past year, member experienced fever past month, serious injury or illness past two years), ii) indicators of health information (participation in health education, use of alternative malaria prevention strategies such as window netting, absence of stagnant water and bushes near house), iii) measure of income (quartiles of consumption expenditure), iv) measure of socio-economic status (major occupation of the head, demographic features, different housing characteristics).*

Another potential econometric concern with our analysis is related to the fact that both insurance and bed net uptake are choice variables. Smith & Goodwin (1996) noted in the context of crop insurance that these two choice variables could be simultaneously determined in which case a recursive structure, where only insurance is allowed to affect bed net ownership and use, is biased. However, this seems a minor problem in our case, given that malaria is only one of many health problems covered by NHIS. It seems implausible that households decide not to take insurance because they plan to acquire and use ITNs. The results presented in panel D of Table 6.5 are related to this, as they zoom in on the effect of insurance only for the subset of families that owned a bed net in both survey rounds, so that anticipated bed net acquisition does not play a role. As in the previous analyses, it appears that insured households have comparatively fewer members sleeping under FTNs and STNs, corroborating the perverse incentive effect. The coefficient for the latter is slightly higher than the estimate in panel B but maintains its statistical significance, while FTN use is still suggestive of ex-ante moral hazard (though not precisely estimated).

Finally, as mentioned earlier, attitudes regarding the causes of malaria or the effectiveness of bed nets may be correlated with both insurance status and use of bed nets. While our descriptive statistics show that misperceptions are more frequent among the uninsured, which lends support to our interpretation, the data for these variables is only in levels (for 2009) and we cannot establish whether there was a diverging trend whereby the uninsured actually improved their awareness between 2007 and 2009. One of the channels that could affect perceptions is health education. Controlling for this in panel C of Table 6.5 did not alter the results. To further corroborate our evidence of ex-ante moral hazard, we regressed the change in outcome variables on the change in insurance, controlling for the list of variables that measure misperception (as in panel C of Table 6.1) in 2009. This robustness check is presented in panel E, Table 6.5. All variables indicate ex-ante moral hazard and, consistent with previous analyses, the number of members who slept under a self-treated net declines significantly as a result of insurance.

### 6.4.3 Insurance, disease burden and health care utilization

In order to assess the seriousness of ex-ante moral hazard in prevention, one would need to scrutinize the extent to which insured households contract malaria more often than uninsured families, resulting from differences in preventive effort. Our data unfortunately do not allow for this. Since insurance increases access to healthcare (and thereby official diagnosis of malaria), the trend in the number of medically indicated malaria cases in the area is not a reliable guide in this respect. Self-reports of malaria are also extremely tricky, as symptoms vary by type of malaria and are shared with other ailments. A simple formal test on fever incidence, however, shows that 44 percent of insured households had a member of their household who experienced fever against 36 percent for the uninsured. The difference is statistically significant at 5 per cent. Due to the possibility of adverse selection into insurance, however, this difference might not be attributable to a decline in preventive measures among the insured.

***Table 6.6***
*Effect of NHIS on disease burden and health care utilization*

| | A day lost due to poor health last month | # of days lost due to poor health last month | Utilized out-patient health care last month | Number of outpatient health care visits | Utilized inpa-tient health care past year |
|---|---|---|---|---|---|
| *Panel A: Household fixed effects* | | | | | |
| Insurance | 0.103<br>(0.065) | 0.501**<br>(0.251) | 0.099*<br>(0.055) | 0.193<br>(0.136) | 0.099**<br>(0.047) |
| No. of observations | 719 | 696 | 736 | 736 | 727 |
| No. of groups | 379 | 379 | 380 | 380 | 379 |
| R-squared (within) | 0.062 | 0.030 | 0.065 | 0.044 | 0.013 |
| *Panel B: Robustness to controlling for time varying covariates, household fixed effects* | | | | | |
| Insurance | 0.125*<br>(0.066) | 0.497**<br>(0.257) | 0.089*<br>(0.053) | 0.196<br>(0.127) | 0.124**<br>(0.048) |
| No. of observations | 693 | 671 | 709 | 709 | 702 |
| No. of groups | 370 | 370 | 371 | 371 | 371 |
| R-squared (within) | 0.105 | 0.056 | 0.121 | 0.104 | 0.128 |

*Notes: ***, **, * represent statistical significance at 1, 5 and 10 per cent level; Robust standard errors in parentheses; In panel B, time varying covariates controlled for include i) measures of socio-economic status (ownership status of house, number of rooms and dwelling units in the house), ii) measures of health shocks (serious injury or illness in past two years), iii) indicators of health information (participation in health education, use of window netting), iv) presence of stagnant water/ bushes around the house v) measures of demographic features: share of female members, share of children below 5 and below 15).*

Given that malaria is the leading cause of Ghana's morbidity and mortality, we prefer to look into an alternative measure, i.e., days lost to poor health (DLPH), which indicates the overall disease burden that households face. Hence, we estimate the effect of insurance on i) whether or not a household lost a day of work by a sick member due to poor health in the last month, and ii) the number of DLPH in the last month. A fixed effects model is employed to control for a number of time-invariant determinants of adverse selection to insurance. Our result for both outcome variables shows that insured households face a higher disease burden (Table 6.6, panel A, columns 1-2). In analogy to the analysis for bed net adoption in Table 6.5, we also take up more volatile unobservables such as health shocks in the model, which is reported in the first two columns of panel B, Table 6.6. It can be observed that the earlier result remains intact after inclusion of these variables. A decline in preventive measure due to insurance is a plausible explanation for the higher disease burden of those who gained insurance vis-à-vis the uninsured.

If ex-ante moral hazard has indeed led to increased malaria incidence (and possibly that of other diseases via a weakened immunity system), it should be reflected in higher health care utilization. In order to check if our model captures effects where we would expect these, we employ a fixed effect model in panel A of Table 6.6 (columns 3-5) to estimate the effect of insurance on i) whether a household has utilized outpatient health care in the last month, ii) the number of outpatient health care visits made in the last month, and iii) whether the household utilized inpatient health care in the past 12 months. Our estimates show that insured households utilize both more outpatient and inpatient health care. The estimate for frequency of outpatient health care is not precisely estimated at conventional levels but the coefficient is large and positive. We performed a similar robustness check to inclusion of time-varying covariates in panel B and results do not change nominally as a result. While there are concerns over ex-post moral hazard in the insurance literature, this increased health care utilization might not only be due to increased access NHIS provides, but in fact emerge from a genuine health care need as a result of a reduced commitment to prevention.

## 6.5 Conclusion

The existence of ex-ante moral hazard in health insurance is a problem that is often acknowledged but as the same time trivialized without proper empirical underpinning. Our empirical analysis of the impact of the Ghanaian National Health Insurance Scheme on malaria prevention shows that such trivialization is unwarranted, or at least premature. We find that insured households in two districts of Central Ghana are less likely to sleep under a self-treated net and, despite lack of precision, our estimates for bed net ownership and sleeping under a factory-treated net point in the same direction.

Unlike previous impact studies on NHIS, our analysis is based on panel rather than cross-sectional data, which allows to control for time-invariant unobservable factors that influence both insurance and bed net uptake. The non-randomness of insurance uptake called for a propensity score matching method and we employed both non-parametric estimation as well as a propensity adjusted fixed effects model to estimate the effect of health insurance on bed net ownership and use. The results from our main specifications are confirmed by various robustness checks and are in line with qualitative information obtained in a sub-set of the communities that are included in the study. As much as people see disutility of illness, a high level of inconvenience is reported in sleeping under bed nets and the cost-benefit analysis under insurance seems to tip towards treatment at the cost of prevention for a non-trivial part of the sample.

At the same time, we acknowledge that the present analysis does not yet provide a definite answer to the existence of perverse incentives in the location under study. First of all, the data do not allow us to scrutinize the extent to which insured households contract malaria more often than uninsured families due to a decline in prevention efforts. Our findings that insured households face a higher disease burden and that enrollment has been accompanied by increased health care utilization are at least consistent with the presence of ex-ante moral hazard, however.

A second issue that needs further probing concerns the fact that the observed decline in the use of self-treated nets among the newly insured is only weakly reflected in the utilization trend of factory-treated nets. While STNs require more recurrent cost and effort, and therefore more susceptible to perverse incentives, we cannot rule out that other mechanism are at work. For example, the availability of FTNs as compared to that of STNs has grown substantially nation-wide, where the latter are gradually disappearing from the market. If this is also true for the location under study, it opens up the possibility that those who remained uninsured tended to cling to their STN longer (and thus delayed switching to FTNs) compared to those who gained insurance. A relative lack of resources would be an obvious explanation, but since insurance uptake during the period under consideration was concentrated among the poorest households in the sample, an explanation in this direction does not entirely satisfy. This notwithstanding, more insight in local supply trends and acquisition patterns of bed nets is necessary to further validate our findings. More generally, the complexity of factors involved in both the decision to take up insurance as well as in defining one's mix of malaria prevention strategies warrants more extensive qualitative work to ensure that no relevant factors have been overlooked.

Despite these pending issues, we feel it is important to highlight ex-ante moral hazard as a potential backlash effect from the progress achieved by NHIS in opening up curative care for large sections of the population. If our results are corroborated and excess demand follows from reduced prevention, this holds risks for the scheme's financial sustainability as well as for the quality of services delivered. Educational and awareness-raising programs may go some way in redressing the balance of prevention versus treatment, but the introduction of incomplete coverage, such as through co-payments, seems a more cost-effective strategy to neutralize perverse incentives. The latter likely implies a trade-off with the goal of broadening health access for the poor, however.

We believe our paper underscores the importance of considering the unintended behavioral consequences of development interventions due to changes in incentive structures. This reduces the risk that perverse side-effects gradually undermine the success of programs that bring substantial benefits to their target group, as in the case of Ghana's pioneering health insurance system.

## Notes

[1] This paper has been published in *Social Science and Medicine, Vol. 75(1), (2012): pages 138-147*. The manuscript benefited from useful comments and suggestions at the IDEP/LAGV Conference in Public Economics, Marseille, France (June 2011) and at the ISS Research in Progress seminar, The Hague, The Netherlands (February 2011). The paper is co-authored with Luuk van Kempen and Thomas De Hoop. We thank Arjun Bedi, Ruerd Ruben and two anonymous referees for helpful comments on an earlier version.

# 7 Summary and Conclusion

This thesis dealt with five issues related to the economics of health-risk and health insurance. These included, investigating if and why coping responses for health shocks are different from other shock types, identifying the channels of impoverishment due to ill-health, analyzing the impact of Ethiopia's pilot CBHI scheme on household economic welfare, examining the presence and implication of adverse selection in the voluntary CBHI scheme and finally, investigating whether or not the Ghanian NHI suffers from problems of ex-ante moral hazard. Three rounds of panel household survey data (one baseline and two follow up) and in depth event-history interviews were employed in four of the essays on Ethiopia. The last chapter on Ghana was based on two rounds of panel household survey data and on qualitative information gathered from community meetings.

Chapter two investigated which shocks trigger which coping responses and why. There were clear differences in terms of coping strategies across shock types. Coping with relatively idiosyncratic health shocks was met by reductions in savings, asset sales and especially a far greater reliance on borrowing as compared to other shocks. Reductions in food consumption, a prominent response in the case of natural and economic shocks was notably absent in the case of health shocks. The analysis clearly showed that informal safety nets and reliance on friends and family for support, at least in the form of gifts, even in the case of idiosyncratic shocks was absent. While informal borrowing to deal with idiosyncratic shocks did appear to provide some assistance, it was often avoided. The chapter concluded by noting that the relative insensitivity of food consumption to health shocks, as noted in previous studies, does not imply insurability but indicates that it is not a viable response to such a shock as it does not provide cash to meet health care needs. From a policy perspective, the results suggest that at least in the Ethiopian context, the introduction of a formal protection system to deal with health risks is well-founded as informal insurance mechanisms do not seem to provide enough support.

Chapter three focused on the channels of impoverishment due to a variety of ill-health measures. To this end, it went beyond the standard reduced form analysis that focuses on quantifying effects on consumption. The study revealed, for example, that incidence of illness of the head of a household, on average, increased annual household health expenditure by an amount equivalent to 4% of annual household consumption expenditure. Although the labor supply of a household head declined due to ill-health, intra-household labor substitution limited the overall reduction in household labor supply. However, possibly due to productivity differences between the head's labor and the substituted labor and diversion of productive resources for health care, there was a decline in household agricultural production. Ill-health was associated with asset depletion, increases in the probability of indebtedness and in the amount of outstanding loans. While households were able to maintain food consumption, imperfect insurance of non-food consumption was observed. This effect was larger for households with the lowest ability to self-insure. The chapter concluded by arguing that maintaining current consumption through borrowing and depletion of assets and savings is unlikely to be sustainable in the long run and displays the need for interventions that work towards reducing the financial consequences of ill-health. Similar to the conclusion reached in chapter 2, the finding that consumption is maintained by borrowing and selling assets supports the decision to introduce a formal protection system.

After making the case for public interventions, chapter four analysed the impact of the recently introduced pilot, voluntary, CBHI on measures of household economic welfare. Much of the existing evidence on impact of such schemes focuses on health care utilization and out-of-pocket payments, often employing cross-section data and ignoring self-selection. This chapter employed data collected before and after the introduction of the CBHI pilot, to assess the impact of the scheme on household consumption, income, indebtedness and livestock holdings. The study revealed that enrolment leads to a 5 percentage point – or 13 percent – decline in the probability of borrowing and is associated with an increase in household income. Both are outcomes that were found to be affected by ill-health in the preceding chapter. There was no evidence that enrolling in the scheme affected consumption or livestock holdings. The chapter concluded by noting that the scheme enhances household economic welfare by reducing reliance on potentially harmful coping responses such as borrowing. In related work, Mebratie et al. (2013b) find that the CBHI scheme leads to greater health-care utilization and reduces the cost of accessing health care. These complementary findings, that is, the effect of the scheme on enhancing economic welfare and increasing access to health care, support a scaling up of the CBHI scheme.

Chapter five and six examined potential problems of information asymmetry in the provision of health insurance. The presence and implications of adverse selection in the Ethiopian pilot CBHI scheme were examined in chapter five. For this, the chapter employed an innovative approach of eliciting beliefs about future spending on health care. The study showed that households do base expectations regarding future medical expenditure on past spending levels. Despite evidence that households are able to anticipate health care expenses, at least to some extent, there was little or no evidence that expectations influence the decision to take out health insurance. The results presented in this essay suggest that, based on its current design, financial viability of the CBHI scheme is unlikely to be affected by adverse selection.

Chapter six examined an empirically underexplored but theoretically acknowledged incentive problem in health insurance-- ex-ante moral hazard. The chapter investigated whether enrolment in the Ghanaian National Health Insurance Scheme (NHIS) negatively affects ownership and the use of insecticide-treated bed nets (ITNs), the most prominent malaria prevention strategy in malaria endemic areas. The analysis showed that ex-ante moral hazard is present, especially when the level of effort and cost required for prevention is high. The chapter concluded by highlighting concerns regarding unintended consequences of development interventions. Although not definitive, ex-ante moral hazard (changes in preventive behaviour) may be a concern for CBHI schemes as is found in the Ghanaian NHI. While the introduction of co-payments is the most straight forward policy implication to internalize externalities with respect to health-risk prevention, it is likely to compromise the move towards Universal Health Coverage. Complementary interventions (such as health education and awareness programs) maybe needed to reduce the implications of such perverse incentives.

# Appendices

*Figure A2.1*
*Number of shocks experienced by shock type*
*(% of households)*

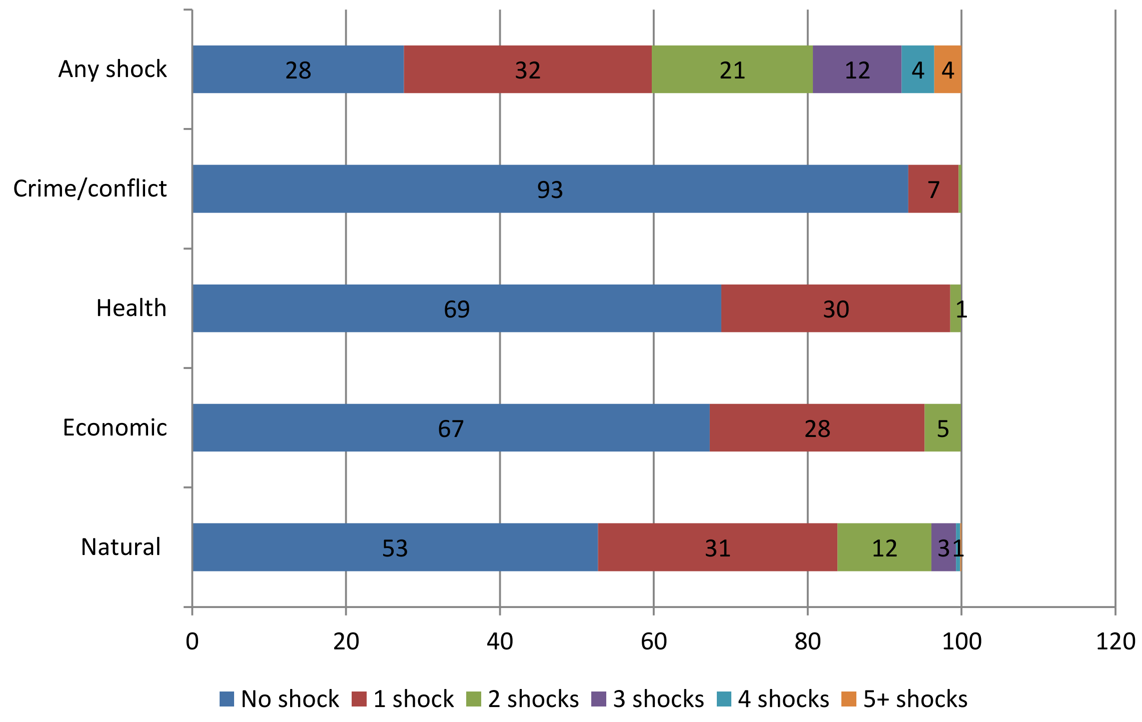


**Table A2.1**
*Probability of relying on a specific coping response*

| VARIABLES | (1) Dissaved | (2) Reduced Consumption | (3) Sold asset | (4) Borrowed | (5) Received Support | (6) Adjusted labor supply | (7) No response |
|---|---|---|---|---|---|---|---|
| ***Shocks*** | | | | | | | |
| Crime/ conflict/family | 0.0861 | 0.0320 | 0.142** | -0.0240 | 0.0117 | -0.00464 | 0.173*** |
| | (0.0596) | (0.0683) | (0.0586) | (0.0316) | (0.0161) | (0.0192) | (0.0608) |
| Health shock | 0.174*** | 0.0201 | 0.170*** | 0.152*** | 0.0336*** | 0.0137 | 0.0314 |
| | (0.0480) | (0.0481) | (0.0407) | (0.0236) | (0.0116) | (0.0128) | (0.0420) |
| Economic shock | 0.267*** | 0.241*** | 0.0979*** | 0.0678*** | 0.00403 | -0.00512 | 0.227*** |
| | (0.0408) | (0.0435) | (0.0372) | (0.0247) | (0.00599) | (0.0128) | (0.0403) |
| Natural shock | 0.301*** | 0.406*** | 0.162*** | 0.0348 | 0.00232 | -0.00218 | 0.0693** |
| | (0.0480) | (0.0453) | (0.0356) | (0.0234) | (0.00586) | (0.0127) | (0.0351) |
| ***Demographics*** | | | | | | | |
| Household size | -0.00108 | 0.0180 | -0.0157* | -0.00774 | -0.00175 | 0.00298 | 0.0240*** |
| | (0.00898) | (0.0111) | (0.00892) | (0.00512) | (0.00204) | (0.00338) | (0.00768) |
| Adult share | -0.0191 | 0.00655 | -0.172** | 0.0426 | 0.00778 | 0.0227 | 0.0838 |
| | (0.102) | (0.120) | (0.0730) | (0.0620) | (0.0210) | (0.0308) | (0.0937) |
| Elderly share | 0.330* | 0.516** | -0.337** | -0.0898 | 0.0466 | 0.0143 | 0.00144 |
| | (0.189) | (0.237) | (0.157) | (0.128) | (0.0335) | (0.0669) | (0.170) |
| Under 5 share | 0.241* | -0.410*** | -0.147 | -0.0292 | -0.0197 | -0.0486 | 0.0567 |
| | (0.130) | (0.138) | (0.108) | (0.0757) | (0.0229) | (0.0514) | (0.106) |
| Male share | 0.107 | 0.0938 | 0.128 | -0.00954 | -0.0304* | -0.0216 | 0.0403 |
| | (0.0851) | (0.0939) | (0.0864) | (0.0483) | (0.0160) | (0.0262) | (0.0844) |
| Head sex | -0.0145 | -0.0189 | 0.00239 | 0.0279 | -0.000156 | -0.00790 | -0.00116 |
| | (0.0530) | (0.0566) | (0.0450) | (0.0294) | (0.00835) | (0.0169) | (0.0498) |
| Head age | -0.00226 | -0.00223 | 0.000879 | 0.000451 | 0.000124 | -0.000920 | 0.00161 |
| | (0.00172) | (0.00192) | (0.00148) | (0.000974) | (0.000262) | (0.000645) | (0.00165) |
| ***Measures of economic status*** | | | | | | | |
| Asset quintile 2 | 0.0345 | -0.0305 | 0.000619 | -0.0304 | -0.00548 | -0.0109 | -0.0224 |
| | (0.0596) | (0.0523) | (0.0557) | (0.0249) | (0.00747) | (0.0134) | (0.0439) |
| Asset quintile 3 | 0.0560 | -0.0848 | -0.0429 | -0.0295 | -0.00959 | -0.000674 | -0.0775* |
| | (0.0606) | (0.0548) | (0.0503) | (0.0306) | (0.00757) | (0.0184) | (0.0449) |
| Asset quintile 4 | 0.0761 | -0.0636 | 0.0739 | -0.0292 | -0.00676 | 0.00880 | -0.0959** |
| | (0.0563) | (0.0603) | (0.0565) | (0.0299) | (0.00861) | (0.0215) | (0.0385) |

**Continued on next page**

***Table A2.1 (continued)***
*Probability of relying on a specific coping response*

| VARIABLES | (1) Dissaved | (2) Reduced Consumption | (3) Sold asset | (4) Borrowed | (5) Received Support | (6) Adjusted labor supply | (7) No response |
|---|---|---|---|---|---|---|---|
| Asset quintile 5 | 0.0821 | -0.137* | 0.0950 | -0.0447 | 0.000407 | -0.00212 | -0.129*** |
| | (0.0690) | (0.0717) | (0.0636) | (0.0341) | (0.0131) | (0.0201) | (0.0468) |
| PSNP beneficiary | -0.0462 | 0.0163 | 0.120** | 0.0732** | 0.00501 | 0.0143 | -0.0718* |
| | (0.0448) | (0.0464) | (0.0483) | (0.0343) | (0.00754) | (0.0149) | (0.0373) |
| Informal education | -0.112** | -0.0222 | 0.0530 | -0.0352 | -0.0132* | -0.00942 | -0.0814** |
| | (0.0476) | (0.0643) | (0.0547) | (0.0328) | (0.00727) | (0.0168) | (0.0401) |
| Primary education | 0.000395 | 0.0279 | 0.00527 | 0.0345 | -0.0115 | 0.00266 | 0.00511 |
| | (0.0412) | (0.0418) | (0.0382) | (0.0225) | (0.00785) | (0.0120) | (0.0349) |
| Secondary (+) education | 0.0640 | 0.172* | 0.0492 | -0.00663 | -0.00712 | -0.0163 | 0.0596 |
| | (0.0777) | (0.0932) | (0.0875) | (0.0426) | (0.0104) | (0.0211) | (0.0632) |
| Social capital | -0.132*** | 0.00948 | 0.0275 | 0.0322 | 0.0312*** | 0.0209* | 0.0388 |
| | (0.0368) | (0.0435) | (0.0389) | (0.0221) | (0.0112) | (0.0126) | (0.0322) |
| Iddir member | 0.119* | -0.0749 | 0.0456 | -0.0122 | -0.0201 | 0.0268 | -0.220* |
| | (0.0719) | (0.0747) | (0.0550) | (0.0394) | (0.0173) | (0.0195) | (0.118) |
| Orthodox | 0.0817 | -0.254*** | -0.0532 | -0.0472 | -0.00917 | 0.0619*** | 0.150*** |
| | (0.0777) | (0.0776) | (0.0538) | (0.0309) | (0.0102) | (0.0223) | (0.0520) |
| Protestant | 0.0308 | -0.233** | 0.102 | 0.00668 | 0.00220 | 0.310* | 0.0185 |
| | (0.0930) | (0.0970) | (0.0851) | (0.0519) | (0.0149) | (0.164) | (0.0887) |
| Other religion | -0.0655 | -0.287*** | 0.111 | 0.0474 | -0.000194 | 0.444 | -0.0533 |
| | (0.129) | (0.0983) | (0.155) | (0.0940) | (0.0211) | (0.292) | (0.0951) |
| Amhara | -0.110 | 0.0970 | -0.0651 | -0.104** | -0.0240** | -0.0758*** | 0.447*** |
| | (0.103) | (0.0940) | (0.0799) | (0.0421) | (0.0102) | (0.0223) | (0.140) |
| Oromiya | 0.0344 | -0.564*** | -0.0948 | -0.0582 | -0.0167** | -0.0283 | 0.504*** |
| | (0.114) | (0.0565) | (0.0737) | (0.0421) | (0.00849) | (0.0229) | (0.137) |
| SNNPR | -0.166* | -0.367*** | -0.378*** | -0.0399 | -0.00173 | -0.152*** | 0.773*** |
| | (0.0940) | (0.0906) | (0.0643) | (0.0687) | (0.0207) | (0.0527) | (0.0875) |
| Observations | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 |
| Pseudo R2 | 0.139 | 0.311 | 0.107 | 0.100 | 0.236 | 0.187 | 0.246 |

*Notes: The reference category for the asset quintile dummy is the poorest quintile; the reference category for the measure of human capital is the head of the household has no education at all; the reference category for the religion of the head is Muslim; the reference category for the region dummy is Tigray; the variable "social capital" refers to a dummy variable if the household has someone to rely on at times of shock. Marginal effects from a probit model are reported; clustered standard errors are in parentheses; ***,**,* refer to 1%, 5% and 10% significance, respectively*

***Table A2.2***
*Summary statistics of variables in the regressions*

| ***Variable name*** | ***Variable definition*** | ***Mean*** | ***Std. Dev.*** |
|---|---|---|---|
| Crime/conflict shock | =1 if shock occurred | 0.069 | 0.254 |
| Health shock | =1 if shock occurred | 0.312 | 0.463 |
| Economic shock | =1 if shock occurred | 0.327 | 0.469 |
| Natural shock | =1 if shock occurred | 0.473 | 0.499 |
| Asset quintile 1 | Asset poorest | 0.200 | 0.400 |
| Asset quintile 2 | Asset second poorest | 0.200 | 0.400 |
| Asset quintile 3 | Asset third poorest | 0.200 | 0.400 |
| Asset quintile 4 | Asset second richest | 0.200 | 0.400 |
| Asset quintile 5 | Asset richest | 0.200 | 0.400 |
| PSNP beneficiary | Household is currently a beneficiary of productive safety net program | 0.229 | 0.420 |
| No education | Head has no education | 0.466 | 0.499 |
| Informal education | Head has an informal education | 0.131 | 0.337 |
| Primary education | Head has a primary education | 0.361 | 0.480 |
| Secondary (+) education | Head has a secondary education | 0.042 | 0.201 |
| Household size | | 5.794 | 2.228 |
| Head age | | 46.227 | 14.036 |
| Head sex | Male=1 | 0.860 | 0.347 |
| Male share | Share of male members | 0.502 | 0.191 |
| Adult share | Share of adults aged [15-65] | 0.498 | 0.209 |
| Elderly share | Share of adults aged >65 | 0.049 | 0.149 |
| Under 5 share | Share of adults <=5 | 0.149 | 0.157 |
| Muslim | Head is Muslim | 0.265 | 0.441 |
| Orthodox | Head is Orthodox Christian | 0.517 | 0.500 |
| Protestant | Head is Protestant | 0.194 | 0.395 |
| Other religion | Other head's religion | 0.025 | 0.157 |
| Social capital | Household has someone to rely on if shock happens | 0.381 | 0.486 |
| Iddir member | Member of a traditional association for financial assistance at times of difficulty | 0.717 | 0.451 |

*Note: Note: Sample size is equally distributed across regions*

***Table A2.3***
*Linear probability model with region fixed effects*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Dissaved | Reduced Consumption | Sold asset | Borrowed | Received Support | Adjusted labor supply | No response |
| Crime/conflict/family (0/1) | 0.0874* | 0.0147 | 0.129** | -0.0200 | 0.00951 | -0.00958 | 0.151*** |
| | (0.0496) | (0.0460) | (0.0534) | (0.0277) | (0.0187) | (0.0264) | (0.0489) |
| Health shock (0/1) | 0.162*** | 0.0186 | 0.159*** | 0.147*** | 0.0487*** | 0.0205 | 0.0361 |
| | (0.0421) | (0.0341) | (0.0373) | (0.0226) | (0.0164) | (0.0154) | (0.0368) |
| Economic shock (0/1) | 0.245*** | 0.168*** | 0.0924*** | 0.0589** | 0.00826 | -0.0183 | 0.200*** |
| | (0.0368) | (0.0313) | (0.0342) | (0.0254) | (0.0119) | (0.0197) | (0.0372) |
| Natural shock (0/1) | 0.293*** | 0.318*** | 0.151*** | 0.0445 | 0.0150 | -0.00774 | 0.0727** |
| | (0.0481) | (0.0403) | (0.0349) | (0.0287) | (0.0144) | (0.0196) | (0.0336) |
| Observations | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 |
| R-squared | 0.173 | 0.367 | 0.129 | 0.083 | 0.098 | 0.102 | 0.276 |

*Notes: Standard errors (reported in parentheses) are clustered at kebele level. Selected coefficients from a linear probability model are reported. The specifications include the full set of control variables shown in Table A2.1; ***,**,* refer to 1%, 5% and 10% level of significance, respectively.*

**Table A2.4**
*Linear probability model with kebele fixed effects*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *VARIABLES* | *Dissaved* | *Reduced Consumption* | *Sold asset* | *Borrowed* | *Received Support* | *Adjusted labor supply* | *No re-sponse* |
| Crime/conflict/family (0/1) | 0.0132 | 0.0354 | 0.110* | -0.0219 | 0.00657 | 0.00645 | 0.142** |
| | (0.0547) | (0.0507) | (0.0568) | (0.0353) | (0.0216) | (0.0283) | (0.0544) |
| Health shock (0/1) | 0.150*** | 0.0500 | 0.180*** | 0.155*** | 0.0437*** | 0.0206 | 0.0311 |
| | (0.0435) | (0.0336) | (0.0369) | (0.0237) | (0.0156) | (0.0161) | (0.0407) |
| Economic shock (0/1) | 0.211*** | 0.244*** | 0.144*** | 0.0525* | 0.00297 | -0.000332 | 0.192*** |
| | (0.0383) | (0.0347) | (0.0376) | (0.0289) | (0.0133) | (0.0188) | (0.0451) |
| Natural shock (0/1) | 0.273*** | 0.385*** | 0.184*** | 0.0291 | 0.0198 | 0.0217 | 0.0570 |
| | (0.0531) | (0.0427) | (0.0347) | (0.0318) | (0.0161) | (0.0202) | (0.0393) |
| Observations | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 |
| R-squared | 0.315 | 0.453 | 0.270 | 0.185 | 0.183 | 0.292 | 0.343 |

*Notes: Standard errors (reported in parentheses) are clustered at kebele level. Selected coefficients from a linear probability model are reported. The specifications include the full set of control variables shown in Table A2.1. The specification controls for kebele fixed effects (96 kebele dummies) instead of regional fixed effects. ***,**,* refer to 1%, 5% and 10% level of significance, respectively.*

***Table A2.5***
*Probit model with region fixed effects*

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* |
|---|---|---|---|---|---|---|---|
| *VARIABLES* | *Dissaved* | *Reduced Consumption* | *Sold asset* | *Borrowed* | *Received Support* | *Adjusted labor supply* | *No re-sponse* |
| Crime/ conflict/family shock (#) | 0.0806 | 0.0160 | 0.105** | -0.0254 | 0.00765 | -0.00863 | 0.150*** |
| | (0.0509) | (0.0720) | (0.0526) | (0.0338) | (0.0108) | (0.0192) | (0.0453) |
| Health shock (#) | 0.100** | -0.0172 | 0.138*** | 0.125*** | 0.0229*** | 0.00756 | -0.00553 |
| | (0.0410) | (0.0494) | (0.0382) | (0.0198) | (0.00695) | (0.0102) | (0.0371) |
| Economic shock (#) | 0.180*** | 0.159*** | 0.0495* | 0.0508*** | 0.00123 | -0.00395 | 0.188*** |
| | (0.0303) | (0.0344) | (0.0260) | (0.0189) | (0.00458) | (0.00998) | (0.0276) |
| Natural shock (#) | 0.179*** | 0.268*** | 0.0813*** | 0.0269* | -0.000407 | -0.00984 | 0.0204 |
| | (0.0326) | (0.0404) | (0.0203) | (0.0144) | (0.00339) | (0.00683) | (0.0231) |
| Observations | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 |
| Pseudo R2 | 0.148 | 0.329 | 0.107 | 0.109 | 0.231 | 0.189 | 0.256 |

*Notes: The shock variables are now the number (#) of shocks experienced by a household rather than the incidence of a shock. Standard errors (reported in parentheses) are clustered at kebele level. Selected marginal effects from a probit model are reported The specifications include the full set of control variables shown in Appendix A1; ***,**,* refer to 1%, 5% and 10% level of significance, respectively.*

***Table A2.6***
*Linear probability model with kebele fixed effects*

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* |
|---|---|---|---|---|---|---|---|
| *VARIABLES* | *Dissaved* | *Reduced Con-sumption* | *Sold asset* | *Borrowed* | *Received Support* | *Adjusted labor supply* | *No re-sponse* |
| Crime/ conflict/family shock (#) | 0.0150 | 0.0183 | 0.0865 | -0.0189 | 0.00423 | -0.00130 | 0.137*** |
| | (0.0482) | (0.0452) | (0.0539) | (0.0307) | (0.0187) | (0.0245) | (0.0511) |
| Health shock (#) | 0.0873*** | -0.000307 | 0.137*** | 0.144*** | 0.0348** | 0.00938 | -0.000163 |
| | (0.0321) | (0.0288) | (0.0339) | (0.0236) | (0.0148) | (0.0121) | (0.0330) |
| Economic shock (#) | 0.143*** | 0.164*** | 0.0932*** | 0.0463* | -0.00332 | -0.00386 | 0.168*** |
| | (0.0281) | (0.0247) | (0.0259) | (0.0242) | (0.0133) | (0.0132) | (0.0318) |
| Natural shock (#) | 0.134*** | 0.220*** | 0.103*** | 0.0259 | 0.00673 | 0.00207 | 0.00873 |
| | (0.0235) | (0.0214) | (0.0193) | (0.0198) | (0.00699) | (0.00846) | (0.0251) |
| Observations | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 | 1,175 |
| R-squared | 0.316 | 0.480 | 0.276 | 0.191 | 0.182 | 0.290 | 0.351 |

*Notes: The shock variables are now the number (#) of shocks experienced by a household rather than the incidence of a shock. All standard errors (reported in parentheses) are clustered at Kebele level. Selected coefficients from a linear probability model are reported. The specifications include the full set of control variables shown in Appendix A1; ***,**,* refer to 1%, 5% and 10% level of significance, respectively.*

***Table A3.1***
*Effect on health expenditure, labor supply and income*
*(robustness check for inclusion of CBHI)*

| | ***Health expenditure*** | ***Labor supply (head)*** | ***Labor supply (others)*** | ***Labor supply (household)*** | ***Crop output*** | ***Total income*** |
|---|---|---|---|---|---|---|
| ADL index | 1,670*** | -17.01* | 36.56 | 25.16 | -3,132 | -3,484 |
| | (540.8) | (9.528) | (30.15) | (35.63) | (2,049) | (2,469) |
| Prolonged illness | 1,108*** | 1.406 | 20.95 | 21.39 | -1,247* | -805.7 |
| | (301.9) | (4.766) | (12.94) | (14.22) | (638.4) | (1,931) |
| Illness | 876.3*** | -0.188 | 16.68** | 15.84 | -2,017** | -591.8 |
| | (168.6) | (3.316) | (7.918) | (9.751) | (910.2) | (852.2) |
| (Very) poor SAH | 792.4*** | -12.23*** | 10.62 | -4.476 | -1,232* | -1,559 |
| | (253.7) | (4.638) | (14.82) | (17.33) | (688.4) | (1,005) |

*Notes: Each coefficient is from a separate linear regression of equation (3.1). Number of observations ranges between [2662-3104]. Not reported but included in the specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

### *Table A3.2*
*Effect on health expenditure, labor supply, income and loans*
*(Quartic root dependent variable)*

| | ***Health expenditure*** | ***Labor supply (head)*** | ***Labor supply (others)*** | ***Labor supply (household)*** | ***Crop output*** | ***Total income*** | ***Loan amount*** |
|---|---|---|---|---|---|---|---|
| ADL index | 1.548** | -0.777*** | 0.0783 | -0.139 | -1.091** | -0.873 | 1.046** |
| | (0.614) | (0.167) | (0.242) | (0.191) | (0.448) | (0.530) | (0.405) |
| Prolonged illness | 1.919*** | -0.144 | 0.138 | 0.0713 | -0.532*** | -0.469* | 0.515** |
| | (0.268) | (0.0886) | (0.120) | (0.0842) | (0.179) | (0.250) | (0.213) |
| Illness | 2.314*** | -0.127** | 0.217*** | 0.0938* | -0.277** | -0.253* | 0.609*** |
| | (0.176) | (0.0500) | (0.0726) | (0.0485) | (0.120) | (0.134) | (0.146) |
| (Very) poor SAH | 1.481*** | -0.396*** | 0.0945 | -0.0918 | -0.370** | -0.473** | 0.555*** |
| | (0.302) | (0.0820) | (0.138) | (0.0937) | (0.171) | (0.191) | (0.206) |

*Notes: Each coefficient is from a separate linear regression of equation (3.1). Number of observations ranges between [2664-3110]. Not reported but included in the specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. All dependent variables are have undergone a quartic root transformation. Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

***Table A3.3***

*Effect on health expenditure:*
*Poison fixed effects and two part models*

| | *Poisson fixed effects* | *Two part models: Cross-section* | | |
|---|---|---|---|---|
| | | *Probit (First part)* | *OLS in log (Second part)* | *GLM (second part)* |
| ADL index | 2.600*** | 0.280*** | 1.087*** | 1.559*** |
| | (0.556) | (0.0711) | (0.288) | (0.309) |
| Prolonged illness | 1.483*** | 0.384*** | 0.534*** | 0.628*** |
| | (0.211) | (0.0307) | (0.104) | (0.123) |
| Illness | 1.562*** | 0.484*** | 0.321*** | 0.340*** |
| | (0.159) | (0.0240) | (0.0836) | (0.102) |
| Poor/very poor SAH | 0.996*** | 0.304*** | 0.342*** | 0.483*** |
| | (0.210) | (0.0363) | (0.111) | (0.134) |

*Notes: Each coefficient is from a separate regression. Number of observations for the first column ranges between [2821-2849]. Number of observations for the first part of the two part models ranges between [4750-4767]. For the second part it ranges between [1444-1453]. Control variables include measures of economic status, human capital, social capital, demographics, religion, shock dummies, year dummies and village dummies. Robust standard errors [column 1] and standard errors clustered at Kebele/village level [column 2-4] are reported in parentheses.*

*GLM is estimated using log link and gamma distribution.*

*Statistical significance: *10%, ** 5%, *** 1%.*

**Table A3.4**
*Effect on health expenditure, labor supply, income and loan*
*(Log (Y+1) dependent variable)*

| | Health expenditure | Labor supply (head) | Labor supply (others) | Labor supply (household) | Crop output | Total income | Loan amount |
|---|---|---|---|---|---|---|---|
| ADL index | 1.415** | -1.123*** | 0.0671 | -0.241 | -0.851** | -0.629 | 1.193** |
| | (0.646) | (0.245) | (0.328) | (0.251) | (0.336) | (0.405) | (0.471) |
| Prolonged illness | 2.118*** | -0.218* | 0.174 | 0.0730 | -0.342** | -0.399** | 0.615** |
| | (0.288) | (0.128) | (0.165) | (0.110) | (0.154) | (0.179) | (0.246) |
| Illness | 2.732*** | -0.195*** | 0.305*** | 0.117* | -0.127 | -0.217** | 0.676*** |
| | (0.193) | (0.0719) | (0.100) | (0.0609) | (0.0978) | (0.0998) | (0.161) |
| (Very) poor SAH | 1.641*** | -0.572*** | 0.128 | -0.130 | -0.266* | -0.375** | 0.620** |
| | (0.322) | (0.118) | (0.188) | (0.117) | (0.141) | (0.147) | (0.237) |

*Notes: Each coefficient is from a separate linear regression of equation (3.1). Number of observations ranges between [2664-3110]. Not reported but included in the specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. All dependent variables are log-transformed (log(Y+1)). Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

### *Table A3.5*
*Effect on indebtedness and asset stock (robustness check for CBHI inclusion)*

| | *Any loan* | *Loan amount* | *Goat* | *Sheep* | *Bulls* | *Calves* | *Oxen* |
|---|---|---|---|---|---|---|---|
| ADL index | 2.646** | 420.9** | -0.203 | -0.622** | -0.0656 | -0.170 | -0.165* |
| | (1.209) | (188.0) | (0.377) | (0.284) | (0.0856) | (0.109) | (0.0889) |
| Prolonged illness | 1.680** | 105.7 | -0.149 | -0.181 | 0.000665 | 0.0274 | -0.0505 |
| | (0.349) | (92.92) | (0.137) | (0.141) | (0.0463) | (0.0623) | (0.0351) |
| Illness | 2.065*** | 277.4*** | -0.0538 | -0.0569 | 0.0200 | -0.0131 | -0.0323 |
| | (0.302) | (86.24) | (0.0982) | (0.110) | (0.0468) | (0.0442) | (0.0290) |
| Poor/very poor SAH | 1.813*** | 289.0** | -0.127 | -0.364** | -0.0126 | -0.0406 | -0.0197 |
| | (0.383) | (133.4) | (0.130) | (0.167) | (0.0492) | (0.0646) | (0.0394) |

*Notes: Each coefficient is from a separate regression of equation (3.1). The column labelled, "Any loan", contains odds ratios from a logit fixed-effects model. Number of observations for this column ranges between [1892-1926]. The rest of the coefficients are from linear regression estimates of (3.1). Number of observations for these ranges between [3061-3108]. Not reported but included in the specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

***Table A3.6***
*Consumption insurance*
*(robustness check for CBHI inclusion)*

| | | ***Total*** | ***Food*** | ***Non-food*** |
|---|---|---|---|---|
| ADL index | Full sample | 0.117 | 0.159* | 0.167 |
| | | (0.0787) | (0.0814) | (0.117) |
| | Poor | -0.132 | -0.0857 | -0.165 |
| | | (0.139) | (0.153) | (0.210) |
| | Non-poor | 0.222** | 0.279*** | 0.280** |
| | | (0.0952) | (0.0908) | (0.136) |
| Prolonged illness | Full sample | 0.00450 | 0.0198 | -0.0840* |
| | | (0.0294) | (0.0329) | (0.0454) |
| | Poor | -0.0808 | -0.0750 | -0.150* |
| | | (0.0517) | (0.0654) | (0.0888) |
| | Non-poor | 0.0406 | 0.0589 | -0.0540 |
| | | (0.0430) | (0.0449) | (0.0647) |
| Illness | Full sample | 0.000358 | 0.00913 | -0.0332 |
| | | (0.0286) | (0.0293) | (0.0354) |
| | Poor | -0.0551 | -0.0392 | -0.0509 |
| | | (0.0628) | (0.0618) | (0.0764) |
| | Non-poor | 0.0108 | 0.0186 | -0.0338 |
| | | (0.0303) | (0.0318) | (0.0395) |
| (Very) poor SAH | Full sample | 0.0114 | 0.0257 | -0.00929 |
| | | (0.0383) | (0.0392) | (0.0513) |
| | Poor | -0.121 | -0.0931 | -0.266*** |
| | | (0.0794) | (0.0838) | (0.0927) |
| | Non-poor | 0.0569 | 0.0686 | 0.0766 |
| | | (0.0429) | (0.0437) | (0.0554) |

*Notes: Each coefficient is from a separate linear regression of equation (3.1). Number of observations for the full sample, 'poor' sample and 'non-poor' sample range between [2934-3075], [747-783] and [2187-2292] respectively. Not reported but included in our specification are village fixed effects and measures of economic status, human capital, social capital, demographics, religion, year and shock dummies. All dependent variables are log-transformed. Clustered standard errors (at Kebele/village level) are reported in parentheses.*

*Statistical significance: * 10%, ** 5%, *** 1%.*

***Table A4.1***
*Welfare effects of CBHI (robustness to excluding covariates)*

| | FE before matching | | | FE after matching | | |
|---|---|---|---|---|---|---|
| | All districts | control districts | Pilot districts | All districts | control districts | Pilot districts |
| Crop output | 673.6 | 497.8 | 1,105** | 670.2 | 474.1 | 1,112** |
| | (476.8) | (577.5) | (466.0) | (481.7) | (576.5) | (477.6) |
| Total income | 971.6* | 755.7 | 1,484** | 942.1 | 695.2 | 1,466** |
| | (564.7) | (631.3) | (587.8) | (571.3) | (631.8) | (600.5) |
| Total consumption | 25.59 | 24.98 | 20.34 | -1.546 | -3.115 | -8.523 |
| | (28.75) | (33.50) | (32.68) | (20.81) | (26.83) | (24.99) |
| Food consumption | 26.35 | 27.59 | 19.39 | -0.494 | -0.301 | -9.072 |
| | (27.86) | (32.57) | (31.65) | (19.87) | (25.83) | (23.97) |
| Non-food consumption | 0.210 | -1.143 | 2.167 | 0.206 | -1.137 | 2.136 |
| | (2.907) | (3.451) | (3.075) | (2.986) | (3.606) | (3.131) |
| Loan (0/1) | -0.0539** | -0.0572** | -0.0412* | -0.0526** | -0.0537** | -0.0417* |
| | (0.0221) | (0.0237) | (0.0237) | (0.0221) | (0.0231) | (0.0240) |
| Loan amount | -43.50 | -39.48 | -29.20 | -38.95 | -31.77 | -24.24 |
| | (70.60) | (78.52) | (72.77) | (70.79) | (78.63) | (73.35) |
| **Livestock** | | | | | | |
| Goats # | -0.0801 | -0.00357 | -0.111 | -0.0820 | 0.00597 | -0.122 |
| | (0.145) | (0.126) | (0.157) | (0.149) | (0.129) | (0.162) |
| Sheep # | -0.0434 | 0.0190 | -0.0817 | -0.0430 | 0.0176 | -0.0808 |
| | (0.114) | (0.132) | (0.113) | (0.116) | (0.135) | (0.115) |
| Bull # | 0.0445 | 0.0368 | 0.0285 | 0.0471 | 0.0399 | 0.0285 |
| | (0.0352) | (0.0398) | (0.0343) | (0.0357) | (0.0410) | (0.0343) |
| Calves # | 0.00694 | -0.00756 | 0.0164 | -0.000696 | -0.0150 | 0.0111 |
| | (0.0634) | (0.0583) | (0.0631) | (0.0649) | (0.0596) | (0.0649) |
| Oxen # | 0.0558 | 0.0723 | 0.0439 | 0.0559 | 0.0749 | 0.0418 |
| | (0.0474) | (0.0514) | (0.0476) | (0.0484) | (0.0526) | (0.0487) |

*Notes: The column headings refer to the choice of control group: all districts (all non-insured households included), control districts (only non-insured households in control districts included), and pilot districts (only non-insured households in pilot districts included). Standard errors (in parentheses) are clustered at the village level. Range of number of observations: first column (4265-4707), second column (2837-3126), third column (3181-3555), fourth column (4080-4510), fifth column (2734-3019), sixth column (3068-3433). 66 out of 1548 observations are outside the common support region [0.086-0.869]. Statistical significance: *** 0.01, ** 0.05, * 0.1*

***Table A4.2***

*Placebo Test: (Treatment=1 if uninsured lives in pilot district, 0 otherwise)*

| | ***Coefficients (St. errors)*** |
|---|---|
| Crop output | -460.3 |
| | (558.0) |
| Total income | -637.2 |
| | (663.1) |
| Total consumption | -4.244 |
| | (21.75) |
| Food consumption | -1.333 |
| | (20.38) |
| Non-food consumption | -2.904 |
| | (3.091) |
| Loan (0/1) | -0.0176 |
| | (0.0213) |
| Loan amount | -34.51 |
| | (95.76) |
| Goats # | 0.0366 |
| | (0.0888) |
| Sheep # | 0.134 |
| | (0.145) |
| Bull # | 0.0268 |
| | (0.0384) |
| Calves # | 0.0250 |
| | (0.0402) |
| Oxen # | 0.000696 |
| | (0.0391) |

*Notes: All estimates are based on OLS regression of change in outcome variables, controlling for covariates (given in table 4.3) and time dummy. In the case of livestock we exclude the asset index quintiles as the index includes number of livestock. Standard errors (in parentheses) are clustered at the village level. Number of observations ranges from 1561 to 1805.*

*Statistical significance: *** 0.01, ** 0.05, * 0.1*

***Table A5.1***

*Means of medical expenditures and selected covariates by whether observation is dropped due to subjective probability non-response or enumeration error, and whether subjective probabilities exhibit logical inconsistencies*

| | ***Excluded due to non-response / enumeration error*** | | | ***Subjective probabilities exhibit logical inconsistencies*** | | |
|---|---|---|---|---|---|---|
| | Yes (N=89) | No (N=3093) | No difference p-value | Yes (N=432) | No (N=2668) | No difference p-value |
| CBHI enrolled | 27.0% | 33.6% | 0.189 | 19.9% | 35.8% | 0.000 |
| Outpatient expense | 42.1 | 53.7 | 0.648 | 50.8 | 54.1 | 0.788 |
| Inpatient expense | 10.7 | 54.1 | 0.416 | 46.7 | 55.2 | 0.745 |
| Ln (average of Min & Max expected OOP) | 5.615 | 5.944 | 0.008 | 6.002 | 5.934 | 0.196 |
| Et[lnYt+1] | 5.456 | 5.692 | 0.055 | 5.714 | 5.689 | 0.622 |
| Illness > 30 days | 12.4% | 11.9% | 0.895 | 13.9% | 11.6% | 0.177 |
| Sensory impairment | 18.0% | 15.5% | 0.523 | 18.1% | 15.2% | 0.126 |
| Paralysis/mobility problem | 24.7% | 17.7% | 0.088 | 21.8% | 17.1% | 0.019 |
| Death in last year | 2.2% | 1.9% | 0.818 | 1.2% | 2.0% | 0.222 |
| Poor/very poor health | 19.1% | 14.8% | 0.267 | 13.4% | 15.1% | 0.373 |
| Poorest assets quintile group | 36.0% | 19.6% | 0.000 | 30.6% | 17.8% | 0.000 |
| Assets quintile 2 | 13.5% | 20.2% | 0.118 | 15.7% | 20.9% | 0.014 |
| Assets quintile 3 | 21.4% | 20.0% | 0.745 | 21.1% | 19.8% | 0.527 |
| Assets quintile 4 | 12.4% | 20.2% | 0.067 | 18.3% | 20.6% | 0.265 |
| Richest assets quintile group | 16.9% | 20.1% | 0.458 | 14.4% | 20.9% | 0.002 |
| Has bank account | 5.6% | 12.1% | 0.062 | 9.7% | 12.5% | 0.099 |
| Covered by safety net programme | 25.3% | 20.5% | 0.282 | 24.1% | 20.0% | 0.052 |
| Forgone care when sick | 6.7% | 2.5% | 0.013 | 3.7% | 2.3% | 0.089 |
| Minutes to nearest health center | 57.4 | 59.9 | 0.560 | 52.4 | 61.1 | 0.000 |
| Educated head | 46.6% | 54.1% | 0.162 | 54.4% | 54.1% | 0.884 |
| Non-agricultural employment | 2.3% | 3.8% | 0.461 | 5.6% | 3.5% | 0.036 |
| Shock | 39.3% | 47.6% | 0.125 | 48.6% | 47.3% | 0.623 |
| Ln(househod size) | 1.458 | 1.666 | 0.000 | 1.616 | 1.674 | 0.013 |
| Muslim | 15.9% | 26.9% | 0.021 | 20.1% | 28.0% | 0.001 |

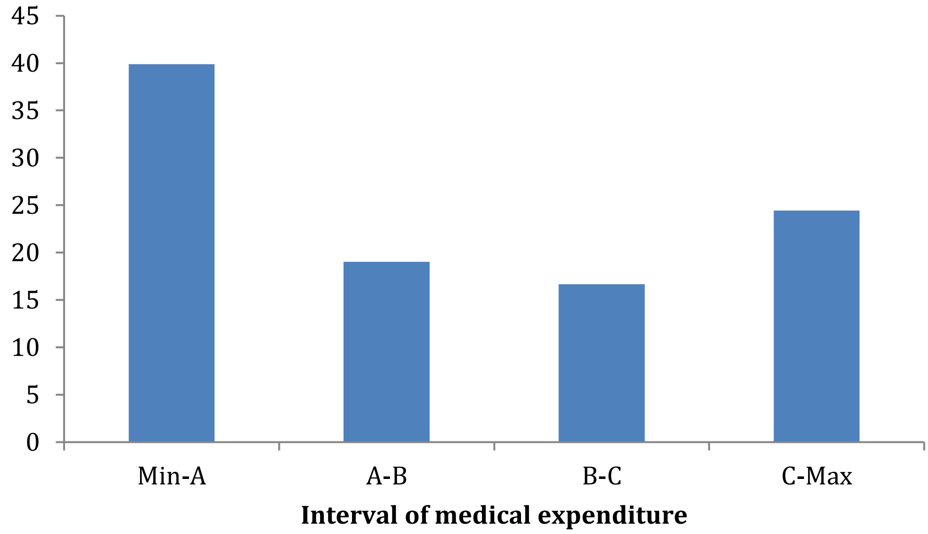
*Note: Definitions of the variables are provided in Table A5.3.*

***Table A5.2***
*Sample statistics of expected and realized medical expenditure, 2013 (ETB)*

| | Cross-section statistics | | | | | |
|---|---|---|---|---|---|---|
| | ***Mean*** | ***Std. dev.*** | ***Min.*** | ***Median*** | ***Max.*** | ***Obs.*** |
| Expected Expenditure (t+1) | | | | | | |
| Mean | 674 | 830 | 16.00 | 390 | 10325 | 1303 |
| Standard deviation | 255 | 427 | 3.14 | 123 | 8443 | 1303 |
| Coeff. of variation | 0.36 | 0.18 | 0.03 | 0.34 | 0.96 | 1303 |
| Realized Expenditure (t) | | | | | | |
| Simple extrapolation | 365 | 1496 | 0 | 0 | 34800 | 1303 |
| Regression extrapolation | 367 | 1095 | ~0 | 120 | 25945 | 1287 |
| If realized expenditure >0 | | | | | | |
| Mean expected expenditure (t+1) | 814 | 923 | 28 | 478 | 7038 | 362 |
| Realized expenditure (t) | 1315 | 2611 | 12 | 510 | 34800 | 362 |

*Notes: Simple and regression extrapolation of realized expenditures refer to method of estimating annual spending on outpatient care from reported expenditure in past two months, as explained in text. Sample size for regression extrapolation is slightly smaller due to missing values on covariates. ETB = Ethiopian Birr, US$1=ETB 18.45 (April 2013)*

***Figure A5.1***
*Sample means of reported probabilities of medical expenditure lying in household-specific intervals, 2013 (N=1303)*




*Notes: A=min+k, B=A+k and C=B+k, where k=(max-min)/4. P(X>A), P(X>B) and P(X>C), where X is medical expenditure, are reported directly for each household, as are min and max. Probability of X lying in each interval is computed from these reported probabilities. Sample restricted to observations for whom correct order of thresholds calculated and responses are logically consistent.*

**_Table A5.3_**
*Summary Statistics of Variables in the Regressions*

| Variable | Description | 2012 (N=1365) Mean | 2012 (N=1365) Std. Dev. | 2013 (N=1303) Mean | 2013 (N=1303) Std. Dev. |
|---|---|---|---|---|---|
| | | | | | |
| CBHI enrolled | Member of community based health insurance | 33.0% | 47.0% | 38.7% | 48.7% |
| Outpatient expense | Out-of-pocket outpatient payment (past 2 months) | 56.5 | 217.3 | 51.5 | 233.1 |
| Inpatient expense | Out-of-pocket inpatient payment (past 12 months) | 54.3 | 541.1 | 56.1 | 503.7 |
| Ln (average of Min & Max expected OOP) | Log of simple average of minimum and maxi-mum expected health expenditure | 5.8 | 1.0 | 6.1 | 1.1 |
| Et[lnYt+1] | Mean of log expected health expenditure | 5.6 | 0.9 | 5.8 | 1.1 |
| Illness > 30 days | At least one member with chronic illness (symp-toms stayed more than 30 days) | 10.6% | 30.8% | 12.7% | 33.3% |
| Sensory impairment | At least one member has difficulty to hear/speak/ or see | 12.6% | 33.2% | 17.9% | 38.3% |
| Paralysis/mobility problem | At least one member has some sort of paralysis or difficulty to stand up after sitting down | 13.6% | 34.2% | 20.8% | 40.6% |
| Death in last year | Household member died in the past 12 months | 2.6% | 15.8% | 1.5% | 12.0% |
| Poor/very poor health | At least one member has poor/very poor self-assessed health | 12.5% | 33.0% | 17.8% | 38.3% |
| Poorest assets quintile group | Asset poorest | 18.6% | 38.9% | 17.0% | 37.6% |
| Assets quintile 2 | Asset second poorest | 20.5% | 40.4% | 21.3% | 40.9% |
| Assets quintile 3 | Asset third poorest | 19.4% | 39.6% | 20.1% | 40.1% |
| Assets quintile 4 | Asset second richest | 20.5% | 40.4% | 20.7% | 40.5% |
| Richest assets quintile group | Asset richest | 21.0% | 40.7% | 20.9% | 40.7% |
| Has bank account | Household has saving bank account | 11.6% | 32.1% | 13.4% | 34.1% |
| Covered by safety net programme | Household member of productive safety net program (PSNP), yes=1, no=0 (a targeted pro-gram in food insecure Woredas) | 20.5% | 40.4% | 19.5% | 39.6% |

*Continued on next page*

***Table A5.3 (continued)***

*Summary Statistics of Variables in the Regressions*

| Variable | Description | 2012 (N=1365) | | 2013 (N=1303) | |
|---|---|---|---|---|---|
| | | Mean | Std. Dev. | Mean | Std. Dev. |
| | | | | | |
| Forgone care when sick | Someone was ill in last two months but did not receive treatment because of one of the following: a) health care/medicines are too expensive b) health facilities are too far c) could not take time off work / lose income | 2.5% | 15.6% | 2.1% | 14.5% |
| Minutes to nearest health center | Travel time to nearest health center (minutes) | 62.8 | 41.3 | 59.3 | 39.9 |
| Educated head | Head has at least informal education | 56.4% | 49.6% | 51.6% | 50.0% |
| Non-agri employment | Head's main occupation: non-agricultural employment | 2.9% | 16.9% | 4.1% | 19.8% |
| Ln(househod size) | Log household size | 1.684 | 0.446 | 1.664 | 0.455 |
| male [<=5] | Share of male aged<=5 | 0.070 | 0.109 | 0.065 | 0.103 |
| female [<=5] | Share of female aged<=5 | 0.068 | 0.113 | 0.062 | 0.103 |
| male [6-18] | Share of male aged [6-18] | 0.198 | 0.163 | 0.202 | 0.169 |
| female [6-18] | Share of female aged [6-18] | 0.186 | 0.161 | 0.184 | 0.160 |
| male [19-45] | Share of male aged [19-45] | 0.155 | 0.137 | 0.150 | 0.139 |
| female [19-45] | Share of female aged [19-45] | 0.162 | 0.119 | 0.161 | 0.122 |
| male [46-60] | Share of male aged [46-60] | 0.044 | 0.081 | 0.046 | 0.087 |
| female [46-60] | Share of female aged [46-60] | 0.051 | 0.109 | 0.057 | 0.122 |
| male [>=61] | Share of male aged >=61 | 0.039 | 0.109 | 0.041 | 0.104 |
| female [>=61] | Share of female aged >=61 | 0.027 | 0.109 | 0.033 | 0.123 |
| Muslim | Religion of the head is Muslim | 27.1% | 44.5% | 29.0% | 45.4% |
| Shock | Household experienced Crime/conflict shock (divorce, land / water conflict, theft of crops, theft of livestock), economic shock (decline in price of output, unemployment, loss of equipment, death of livestock) or natural shock (flood, storm, fire, drought, untimely rain, insect damage) in the past 12 months. | 44.2% | 49.7% | 50.7% | 50.0% |

***Table A5.4***
*Regressions of the Mean of Log Expected Medical Expenditure (separately for each year)*

| | *OLS* | | *LAD* | | *2SLS* | |
|---|---|---|---|---|---|---|
| ***VARIABLES*** | ***2012*** | ***2013*** | ***2012*** | ***2013*** | ***2012*** | ***2013*** |
| Ln(outpatient expense) t | 0.0167 | 0.0243** | 0.0102 | 0.0148 | 0.0495 | 0.138** |
| | (0.0116) | (0.0108) | (0.0146) | (0.0167) | (0.0445) | (0.0682) |
| Ln(outpatient expense) t-1 | 0.0349*** | 0.0254** | 0.00745 | 0.0259 | 0.0366 | 0.00469 |
| | (0.0125) | (0.0116) | (0.0141) | (0.0166) | (0.0301) | (0.0553) |
| Ln(inpatient expense) t | 0.133*** | 0.156*** | 0.125*** | 0.137*** | 0.127*** | 0.140*** |
| | (0.0261) | (0.0337) | (0.0370) | (0.0364) | (0.0261) | (0.0358) |
| Ln(inpatient expense) t-1 | -0.00788 | 0.00978 | -0.00826 | 0.0332 | -0.00710 | 0.00267 |
| | (0.0307) | (0.0301) | (0.0446) | (0.0407) | (0.0302) | (0.0349) |
| Someone in household experienced: | | | | | | |
| Illness > 30 days | 0.171* | 0.244*** | 0.0660 | 0.451*** | 0.125 | 0.167** |
| | (0.0932) | (0.0790) | (0.0951) | (0.124) | (0.107) | (0.0851) |
| Sensory impairment | -0.0387 | 0.00367 | -0.0135 | -0.0208 | -0.0353 | -0.0420 |
| | (0.0853) | (0.0838) | (0.106) | (0.102) | (0.0840) | (0.0876) |
| Paralysis/ mobility problem | 0.0203 | -0.0655 | 0.103 | -0.114 | 0.0132 | -0.0727 |
| | (0.0789) | (0.0654) | (0.0799) | (0.0987) | (0.0800) | (0.0669) |
| Poor/very poor health | 0.00254 | 0.0279 | 0.0395 | -0.0122 | -0.0377 | -0.0731 |
| | (0.104) | (0.0723) | (0.102) | (0.106) | (0.113) | (0.107) |
| Death in last year | 0.122 | 0.232 | 0.135 | 0.363 | 0.129 | 0.271 |
| | (0.166) | (0.202) | (0.179) | (0.302) | (0.165) | (0.215) |
| 2nd poorest assets quintile group | 0.219*** | 0.138* | 0.279** | 0.0651 | 0.214*** | 0.119 |
| | (0.0809) | (0.0761) | (0.114) | (0.105) | (0.0817) | (0.0860) |
| Assets quintile 3 | 0.322*** | 0.165** | 0.425*** | 0.163 | 0.316*** | 0.149* |
| | (0.0826) | (0.0765) | (0.128) | (0.114) | (0.0826) | (0.0780) |
| Assets quintile 4 | 0.454*** | 0.248*** | 0.449*** | 0.180 | 0.443*** | 0.245*** |
| | (0.0913) | (0.0914) | (0.137) | (0.123) | (0.0947) | (0.0907) |
| Richest assets quintile group | 0.613*** | 0.545*** | 0.569*** | 0.542*** | 0.605*** | 0.525*** |
| | (0.0868) | (0.0963) | (0.149) | (0.132) | (0.0910) | (0.0952) |
| Enrolled in PSNP | -0.0740 | -0.0355 | -0.0853 | -0.0654 | -0.0784 | -0.0252 |
| | (0.0709) | (0.0831) | (0.0959) | (0.0900) | (0.0700) | (0.0829) |
| Has bank account | 0.00908 | 0.132 | 0.0313 | 0.173 | 0.00598 | 0.0973 |
| | (0.0813) | (0.0898) | (0.0871) | (0.120) | (0.0808) | (0.0960) |

***Continued on next page***

***Table A5.4 (continued)***
*Regressions of the Mean of Log Expected Medical Expenditure (separately for each year)*

| | OLS | | LAD | | 2SLS | |
|---|---|---|---|---|---|---|
| VARIABLES | 2012 | 2013 | 2012 | 2013 | 2012 | 2013 |
| Non-agricultural employment | 0.292* | -0.0578 | 0.323 | 0.186 | 0.276* | -0.0918 |
| | (0.149) | (0.171) | (0.218) | (0.152) | (0.148) | (0.172) |
| Educated head | 0.135*** | 0.0897 | 0.148** | 0.113 | 0.136*** | 0.101* |
| | (0.0472) | (0.0594) | (0.0668) | (0.0745) | (0.0460) | (0.0609) |
| CBHI enrolled | 0.0834 | -0.00163 | 0.113 | 0.00236 | 0.0887 | 0.0448 |
| | (0.0572) | (0.0590) | (0.0770) | (0.0750) | (0.0556) | (0.0633) |
| Forgone care when sick | -0.131 | -0.138 | -0.227 | -0.158 | -0.120 | -0.0585 |
| | (0.160) | (0.179) | (0.184) | (0.192) | (0.155) | (0.181) |
| Minutes to nearest health center | -0.000760 | 0.00181** | -0.000814 | 0.00125 | -0.000727 | 0.00156* |
| | (0.000586) | (0.000756) | (0.000621) | (0.000917) | (0.000575) | (0.000812) |
| Shock | 0.131** | 0.0481 | 0.185*** | 0.0936 | 0.126** | 0.0600 |
| | (0.0587) | (0.0622) | (0.0601) | (0.0696) | (0.0577) | (0.0639) |
| Ln(household size) | 0.0465 | 0.0739 | 0.214** | 0.152 | 0.0311 | 0.0412 |
| | (0.0775) | (0.0775) | (0.0969) | (0.116) | (0.0787) | (0.0809) |
| Constant | 3.560*** | 3.895*** | 3.595*** | 3.821*** | 3.580*** | 4.050*** |
| | (0.307) | (0.277) | (0.257) | (0.478) | (0.296) | (0.285) |
| Observations | 1,353 | 1,278 | 1,353 | 1,278 | 1,353 | 1,278 |
| R2/Pseudo R2 | 0.300 | 0.427 | 0.163 | 0.261 | | |
| F-test (P-value) for joint significance: | | | | | | |
| All variables | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Health variables | 0.361 | 0.032 | 0.584 | 0.004 | 0.716 | 0.136 |
| Age-sex composition | 0.006 | 0.005 | 0.152 | 0.090 | 0.002 | 0.006 |

*Notes: Regressions also include the share of household member in gender specific age groups and district dummies. Standard errors in parentheses. Corrected for clustering at Kebele level for OLS and 2SLS. Bootstrap standard errors with 200 repetitions for LAD. *** p<0.01, ** p<0.05, * p<0.1*

**Table A5.5**
*Regressions presented in Tables 5.6 and 5.8 with dependent variable being: log of average of minimum and maximum expected medical expenditure*

| | Levels | | | First difference | |
|---|---|---|---|---|---|
| | LAD | OLS | 2SLS | OLS | 2SLS |
| Ln(outpatient expense) t | 0.0240** | 0.0251*** | 0.104* | 0.0424*** | 0.251*** |
| | (0.0111) | (0.00833) | (0.0537) | (0.0149) | (0.0861) |
| Ln(outpatient expense) t-1 | 0.0254** | 0.0392*** | 0.121*** | 0.0522*** | 0.262*** |
| | (0.0122) | (0.00903) | (0.0411) | (0.0158) | (0.0878) |
| Ln(inpatient expense) t | 0.154*** | 0.140*** | 0.128*** | 0.112** | 0.117** |
| | (0.0410) | (0.0228) | (0.0251) | (0.0504) | (0.0542) |
| Ln(inpatient expense) t-1 | -0.00258 | -0.00426 | -0.0203 | -0.0429 | -0.0643 |
| | (0.0253) | (0.0230) | (0.0245) | (0.0480) | (0.0554) |
| Someone in household experienced: | | | | | |
| Illness > 30 days | 0.130 | 0.172** | 0.0594 | 0.0164 | -0.0238 |
| | (0.0886) | (0.0756) | (0.0952) | (0.146) | (0.147) |
| Sensory impairment | 0.0323 | 0.0112 | 0.00769 | -0.0478 | -0.0658 |
| | (0.0852) | (0.0599) | (0.0611) | (0.0952) | (0.108) |
| Paralysis/ mobility problem | -0.0397 | 0.0241 | -0.00416 | 0.177** | 0.160* |
| | (0.0750) | (0.0561) | (0.0600) | (0.0825) | (0.0834) |
| Poor/very poor health | 0.134* | 0.0619 | -0.0444 | 0.0830 | -0.0504 |
| | (0.0805) | (0.0790) | (0.0859) | (0.121) | (0.134) |
| Death in last year | 0.147 | 0.0969 | 0.0500 | 0.168 | 0.205 |
| | (0.183) | (0.133) | (0.142) | (0.248) | (0.273) |
| 2nd poorest assets quintile group | 0.212** | 0.222*** | 0.213*** | 0.0615 | -0.00627 |
| | (0.0933) | (0.0620) | (0.0635) | (0.102) | (0.102) |
| Assets quintile 3 | 0.274*** | 0.314*** | 0.306*** | 0.204 | 0.105 |
| | (0.0944) | (0.0655) | (0.0658) | (0.123) | (0.128) |
| Assets quintile 4 | 0.360*** | 0.422*** | 0.395*** | 0.254** | 0.198 |
| | (0.0962) | (0.0683) | (0.0727) | (0.122) | (0.134) |
| Richest assets quintile group | 0.578*** | 0.660*** | 0.614*** | 0.630*** | 0.589*** |
| | (0.106) | (0.0759) | (0.0798) | (0.152) | (0.155) |
| Enrolled in PSNP | -0.0954 | -0.0259 | -0.0154 | 0.176 | 0.244 |
| | (0.0753) | (0.0569) | (0.0620) | (0.168) | (0.171) |
| Has bank account | 0.00416 | 0.0706 | 0.0591 | 0.195* | 0.267** |
| | (0.0719) | (0.0672) | (0.0691) | (0.118) | (0.118) |

*Continued on next page*

***Table A5.5 (continued)***

*Regressions presented in Tables 5.6 and 5.8 with dependent variable being: log of average of minimum and maximum expected medical expenditure*

| | Levels | | | First difference | |
|---|---|---|---|---|---|
| | LAD | OLS | 2SLS | OLS | 2SLS |
| Non-agricultural employment | 0.242* | 0.142 | 0.117 | 0.196 | 0.108 |
| | (0.138) | (0.127) | (0.124) | (0.235) | (0.245) |
| Educated head | 0.104** | 0.0746* | 0.0642 | 0.123 | 0.0927 |
| | (0.0503) | (0.0400) | (0.0418) | (0.0897) | (0.0959) |
| CBHI enrolled | 0.0515 | 0.0348 | 0.0537 | 0.0234 | 0.0541 |
| | (0.0586) | (0.0453) | (0.0441) | (0.0843) | (0.0797) |
| Forgone care when sick | -0.244 | -0.0551 | -0.0295 | -0.0293 | -0.0660 |
| | (0.186) | (0.121) | (0.128) | (0.167) | (0.192) |
| Minutes to nearest health center | 0.00103 | 0.000781* | 0.000710 | 0.00105 | 0.00108 |
| | (0.000672) | (0.000453) | (0.000483) | (0.00111) | (0.00123) |
| Shock | 0.154*** | 0.147*** | 0.144*** | 0.135* | 0.145* |
| | (0.0551) | (0.0526) | (0.0535) | (0.0794) | (0.0803) |
| Ln(household size) | 0.0185 | -0.0522 | -0.114 | 0.464* | 0.531** |
| | (0.0883) | (0.0708) | (0.0797) | (0.239) | (0.256) |
| Year 2013 | 0.253*** | 0.254*** | 0.285*** | | |
| | (0.0496) | (0.0729) | (0.0697) | | |
| Constant | 3.964*** | 3.840*** | 3.921*** | 0.281*** | 0.336*** |
| | (0.281) | (0.192) | (0.203) | (0.0740) | (0.0677) |
| Observations | 2,631 | 2,631 | 2,631 | 1,097 | 1,097 |
| R-squared | 0.149 | 0.269 | | 0.078 | |
| F-test (P-value) for joint significance: | | | | | |
| All variables | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Health variables | 0.190 | 0.068 | 0.969 | 0.290 | 0.493 |
| Age-sex composition | 0.186 | 0.003 | 0.001 | 0.475 | 0.273 |

*Notes: Regressions also include the share of household member in gender specific age groups. In columns 1-3, district dummies are also included. Standard errors in parentheses. Corrected for clustering at Kebele level for OLS and 2SLS. Bootstrap standard errors with 200 repetitions for LAD. *** p<0.01, ** p<0.05, * p<0.1*

**Table A5.6**
*Regressions of the standard deviation of log expected medical expenditure (first differences)*

| | (1) | | (2) | |
|---|---|---|---|---|
| | OLS | | 2SLS | |
| Ln(outpatient expense) t | -0.00171 | (0.00473) | -0.0184 | (0.0241) |
| Ln(outpatient expense) t-1 | 0.000470 | (0.00451) | -0.00863 | (0.0205) |
| Ln(inpatient expense) t | 0.00854 | (0.0111) | 0.00846 | (0.0110) |
| Ln(inpatient expense) t-1 | -0.00651 | (0.0115) | -0.00558 | (0.0113) |
| Someone in household experienced: | | | | |
| Illness > 30 days | -0.0499* | (0.0290) | -0.0399 | (0.0358) |
| Sensory impairment | -0.0173 | (0.0245) | -0.0149 | (0.0245) |
| Paralysis/ mobility problem | 0.0702*** | (0.0244) | 0.0704*** | (0.0246) |
| Poor/very poor health | 0.000649 | (0.0275) | 0.0128 | (0.0341) |
| Death in last year | 0.0340 | (0.0444) | 0.0258 | (0.0495) |
| 2nd poorest assets quintile group | 0.0243 | (0.0268) | 0.0320 | (0.0313) |
| Assets quintile 3 | 0.0717* | (0.0407) | 0.0811* | (0.0459) |
| Assets quintile 4 | 0.0366 | (0.0405) | 0.0445 | (0.0436) |
| Richest assets quintile group | 0.0813 | (0.0512) | 0.0853 | (0.0521) |
| Enrolled in PSNP | -0.00303 | (0.0428) | -0.00518 | (0.0417) |
| Has bank account | 0.0232 | (0.0239) | 0.0202 | (0.0247) |
| Non-agricultural employment | 0.0476 | (0.0493) | 0.0563 | (0.0502) |
| Educated head | 0.00628 | (0.0226) | 0.00686 | (0.0224) |
| CBHI enrolled | 0.0268 | (0.0236) | 0.0226 | (0.0260) |
| Forgone care when sick | 0.0240 | (0.0468) | 0.0252 | (0.0475) |
| Minutes to nearest health center | 0.000166 | (0.000317) | 0.000148 | (0.000323) |
| Shock | 0.00593 | (0.0175) | 0.00652 | (0.0186) |
| Ln(household size) | 0.123** | (0.0603) | 0.123* | (0.0655) |
| Constant | 0.00271 | (0.0166) | -0.000543 | (0.0171) |
| Observations | 1,097 | | 1,097 | |
| R-squared | 0.029 | | | |
| F-test (P-value) for joint significance: | | | | |
| All variables | 0.004 | | 0.000 | |
| Health variables | 0.026 | | 0.040 | |
| Age-sex composition | 0.196 | | 0.447 | |

*Notes: Regressions also include the share of household member in gender specific age groups. Standard errors in parentheses are corrected for clustering at Kebele level for OLS and 2SLS. *** p<0.01, ** p<0.05, * p<0.1*

***Table A5.7***
*Probit estimates of plans to enrol in CBHI scheme for households not enrolled in 2012 (for each year separately)*

| | 2012 | | 2013 | |
|---|---|---|---|---|
| Mean log expected medical exp. | 0.00816 | (0.0302) | 0.0115 | (0.0310) |
| Std. dev. log expected medical exp. | 0.210** | (0.100) | 0.459*** | (0.107) |
| 2nd poorest assets quintile group | 0.158*** | (0.0599) | 0.108 | (0.0696) |
| Assets quintile 3 | 0.146** | (0.0738) | 0.182*** | (0.0690) |
| Assets quintile 4 | 0.137* | (0.0768) | 0.192** | (0.0746) |
| Richest assets quintile group | 0.0862 | (0.0860) | 0.0493 | (0.0938) |
| Enrolled in PSNP | -0.167* | (0.0887) | 0.203*** | (0.0752) |
| Has bank account | -0.0386 | (0.0827) | -0.137 | (0.0976) |
| Educated head | -0.114*** | (0.0402) | 0.0787 | (0.0586) |
| Official position held (head) | -0.00153 | (0.0504) | 0.196*** | (0.0737) |
| Forgone care when sick | 0.0463 | (0.136) | 0.138 | (0.123) |
| Minutes to nearest health center | 0.000729 | (0.000639) | -0.00137** | (0.000675) |
| Perceived quality of care | -0.130 | (0.0820) | -0.0919 | (0.0708) |
| Ln(household size) | 0.348*** | (0.0785) | 0.0778 | (0.0758) |
| Head is Muslim | -0.100 | (0.0963) | -0.248*** | (0.0697) |
| Tigray region | 0.342*** | (0.0943) | 0.0976 | (0.115) |
| Amhara region | 0.113 | (0.107) | -0.148 | (0.120) |
| Oromiya region | 0.350*** | (0.0952) | 0.190* | (0.106) |
| Observations | 600 | | 468 | |
| Pseudo R2 | 0.153 | | 0.153 | |

*Note: Marginal effects reported. The dependent variable is an indicator of whether the household respondent reported that the household planned to enrol. The models also include the share of household members in gender specific age groups. Standard errors in parentheses are corrected for clustering at Kebele level. *** p<0.01, ** p<0.05, * p<0.1*

# References


Admassie, A., Abebaw, D. and Woldemichael, A.D. (2009). "Impact evaluation of the Ethiopian Health Service Extension Program." *Journal of Development Effectiveness* 1(4): 430-449

Adongo, P.B., Kirkwood, B., & Kendall, C. (2005). "How local community knowledge about malaria affects insecticide-treated net use in Northern Ghana." *Tropical Medicine & International Health*, 10(4), 366-378.

Agyepong, I., & Manderson, L. (1999). "Mosquito avoidance and bed net use in the Greater Accra region, Ghana." *Journal of Biosocial Science*, 31(1), 79-92.

Ahorlu, C.K., Dunyo, S.K., Afari, E.A., Koram, K.A., & Nkrumah, F.K. (1997). "Malaria-related beliefs and behaviour in Southern Ghana: implications for treatment, prevention and control." *Tropical Medicine & International Health*, 2(5), 488-499.

Akazili, J., Aikins, M.., & Binka, F.N. (2007). "Malaria treatment in Northern Ghana: what is the treatment cost per case per household?" *African Journal of Health Sciences*, 14(1-2), 70-79.

Asenso-Okeyere, W.K., Anum, A., Osei-Akoto, I., & Adukonu, A. (1998). "Cost recovery in Ghana: are there changes in health care seeking behaviour?" *Health Policy and Planning*, 13(2), 181-188.

Asfaw, A. and von Braun, J. (2004). "Is consumption insured against illness? Evidence on vulnerability of households to health shocks in Rural Ethiopia." *Economic Development and Cultural Change* 53 (1): 115-129

Attanasio, O. (2009). "Expectations and perceptions in developing countries: their measurement and their use." *American Economic Review: papers and proceedings* 99(2): 87-92.

Attanasio, O. and Augsburg, B. (2012). "Subjective expectations and income processes in rural India." Universtiy College London. Mimeo.

Augurzky, B., & Schmidt, C.M. (2001). "The propensity score: a means to an end." IZA Discussion Papers 271. Bonn: Institute for the Study of Labor.

Bales, S. (2013). "Impact of health shocks on household welfare in Vietnam- estimates using fixed effects estimation." HEFPA Working Paper-18, Institute of Health Policy and Management, Erasmus University Rotterdam

Bellemare M. (2009). "When perception is reality: subjective expectations and contracting." *American Journal of Agricultural Economics* 91(5): 1377–81.

Bhattacharya, J., & Packalen, M. (2008). "The other ex-ante moral hazard in health." NBER Working Paper Series 13863. National Bureau of Economic Research.

Binka, F. N., Kubaje, A., Adjuik, M., Williams, L.A., Lengeler, C., Maude, G.H., et al. (1996). "Impact of permethrin impregnated bed nets on child mortality in Kassena-Nankana district, Ghana: a randomized-controlled trial." *Tropical Medicine & International Health*, 1(2), 147–154.

Breyer, F., Bundorf, M.K. and Pauly, M.V. (2012). "Health care spending risk, health insurance, and payment to health plans." in Pauly, M.V., McGuire, T.G. and Barros, P.P. (Editors) *Handbook of Health Economics*, Volume 2, Chapter 11: 691-762, Elsevier, Amsterdam

Bryson, A., Dorsett, R., & Purdon, S. (2002). "The use of propensity score matching in the evaluation of labour market policies." DWP working papers 4. Department of Work and Pensions, London School of Economics.

Buntin, M.B. and Zaslavsky, A.M. (2004). "Too much ado about two-part models and transformation? Comparing methods of modelling medicare expenditures." *Journal of Health Economics* 23(3): 525-542

Caliendo, M., & Kopeinig, S. (2008). "Some practical guidance for implementation of propensity score matching." *Journal of Economic Surveys*, 22(1), 31-72.

Card, D., Dobkin, C., & Maestas, N. (2008). "The impact of nearly universal insurance coverage on health care utilization: evidence from Medicare." *American Economic Review*, 98(5), 2242-2258.

Chee, G., Smith, K. and Kapinga, A. (2002). "Assessment of community health fund in Hanang District, Tanzania." The Partners for Health Reformplus Project, Abt Associates Inc., Bethesda, MD.

Chetty, R. and Looney, A. (2006). "Consumption smoothing and the welfare consequences of social insurance in developing economies." *Journal of Public Economics* 90(12): 2351-2356

Chiappori, P. A. (2000). "Econometric models of insurance under asymmetric information." In Dionne, G. (Ed.), *Handbook of insurance*, pp. 363-392. Kluwer Academic Publishers, Norwell, MA.

Cochrane, J. (1991). "A simple test of consumption insurance." *The Journal of Political Economy* 99(5): 957-976

Cohen, A., & Dehejia, R. (2004). "The effect of automobile insurance and accident liability laws on traffic fatalities." *Journal of Law and Economics*, 47(2), 357-393.

Courbage, C., & De Coulon, A. (2004). "Prevention and private health insurance in the UK." *Geneva Papers on Risk and Insurance: Issues and Practice*, 29(4), 719-727.

Cutler, D.M., & Zeckhauser, R. (2000). "The anatomy of health insurance." In A.J. Cuyler, & J.P. Newhouse (Eds.), *Handbook of Health Economics* (pp. 563-643). North-Holland: Elsevier.

D'Alessandro, U., Olaleye, B., Langerock, P., Aikins, M.K., Thomson, M.C., Cham, M.K., et al. (1995). "Mortality and morbidity from malaria in Gambian children after introduction of an impregnated bed net programme." *The Lancet*, 345(8948): 479-483.

Dave, D., & Kaestner, R. (2009). "Health insurance and ex-ante moral hazard: evidence from Medicare." *International Journal of Health Care Finance and Economics*, 9(4): 367-390.

Davies, S. (2010). "Do shocks have a persistent impact on consumption? The case of rural Malawi." *Progress in Development Studies* 10(1): 75-79

Dehejia, R., & Wahba, S. (2002). "Propensity score-matching methods for non-experimental causal studies." *The Review of Economics and Statistics*, 84(1): 151-161.

De Hoop, T., & Van Kempen, L. (2010). "Trust in health providers as a catalyst for malaria prevention: heterogeneous impacts of health education in rural Ghana." *The Developing Economies*, 48(3): 376-404.

Dekker, M. (2004). "Sustainability and resourcefulness: support networks during periods of crisis." *World Development* 32(10): 1735-1751

Dekker, M. and Wilms, A. (2010). "Health insurance and other risk-coping strategies in Uganda: the case of Microcare Insurance Ltd." *World Development* 38(3): 369-378

Dercon, S. (2004). "Growth and shocks: evidence from rural Ethiopia." *Journal of Development Economics* 74(2): 309-329

Dercon, S., Hoddinott, J. and Woldehanna, T. (2005). "Shocks and consumption in 15 Ethiopian Villages, 1999-2004." *Journal of African Economies* 14(4): 559-585

Dercon, S. and Krishnan, P. (1998). "Changes in poverty in rural Ethiopia 1989-1995: measurement, robustness tests and decomposition." CSAE WPS/98-7, University of Oxford

Delavande A. (2008). "Pill, patch, or shot? Subjective expectations and birth control choice." *International Economic Review* 49(3): 999-1042.

Delavande, A. (2014). "Probabilistic expectations in developing countries." *Annual Review of Economics*, 6(1): 1-20.

Delavande, A., Gine, X. and McKenzie, D. (2011). "Measuring subjective expectations in developing countries: A critical review and new evidence." *Journal of Development Economics* 94(2): 151-163.

Delavande, A. and Kohler, H-P. (2012). "The Impact of HIV testing on subjective expectations and risky behavior in Malawi." *Demography* 49(3): 1011-1036.

de Paula A, Shapira G, Todd P. (2014). "How beliefs about HIV affect risky behaviors: evidence from Malawi." *Journal of Applied Econometrics* 29(6): 944-964

De Weerdt, J. and Dercon, S. (2006). "Risk-sharing networks and insurance against illness." *Journal of Development Economics* 81(2): 337-356

Diop, F., Sulzbach, S. and Chankova, S. (2006). "The impact of Mutual Health Organizations on social inclusion, access to health care, and household income protection: evidence from Ghana, Senegal, and Mali." PHRplus, Abt Associates Inc, Bethesda.

Dominitz, J. (2001). "Estimation of income expectations models using expectations and realization data." *Journal of Econometrics* 102(2): 165-195

Dominitz, J. and Manski, C.F. (1997). "Using expectations data to study subjective income expectations." *Journal of the American Statistical Association* 92(439): 855-867

Ekman, B. (2004). "Community Based Health Insurance in low-income countries: a systematic review of the evidence." *Health Policy and Planning*, 19(5): 249-270.

Fafchamps, M., Udry,C. and Czukas, K. (1998). "Drought and saving in West Africa: are livestock a buffer stock?" *Journal of Development Economics* 55(2): 273-305

Feenberg, D. and Skinner, J. (1994). "The risk and duration of catastrophic health care expenditures." *The Review of Economics and Statistics* 76(4): 633-647.

Flores, G., Krishnakumar, J., O'Donnell, O., and van Doorslaer E. (2008). "Coping with health-care costs: implications for the measurement of catastrophic expenditures and poverty." *Health Economics* 17(12): 1393-1412

Flores, G. and O'Donnell, O. (2013). "Catastrophic medical expenditure risk." Tinbergen Institute Discussion Paper TI 2012-078/3, Amsterdam: Tinbergen Institute

FMoH. (2005). "Health Sector Strategic Plan (HSDP-III) 2005/6-2009/10." Planning and Programming Department, Addis Ababa.

FMoH (2008). "Health Insurance Strategy." Federal Ministry of Health Planning and Program Department. Addis Ababa.

FMoH. (2010, April). "Ethiopia's Fourth National Health Accounts, 2007/2008". Addis Ababa

Fortin, B., & Lanoie, P. (2000). "Incentive effects of workers' compensation: a survey." In G. Dionne (Ed.), *Handbook of Insurance* (pp. 421-454). Boston: Kluwer.

Foster, A. D. (1994). "Poverty and illness in low-income rural areas." *The American Economic Review* 84(2): 216-220

French, E. and Jones, J. B. (2004). "On the distribution and dynamics of health care costs." *Journal of Applied Econometrics* 19(6): 705-721.

Genoni, M.E. (2012). "Health shocks and consumption smoothing: evidence from Indonesia." *Economic Development and Cultural Change* 60(3): 475-506

Gertler, P. and Gruber, J. (2002). "Insuring consumption against illness." *The American Economic Review* 92(1): 51-70

Gertler, P., Levine, D. and Moretti E. (2009). "Do microfinance programs help families insure consumption against illness?" *Health Economics* 18(3): 257-273

Gimnig, J. E., Kolczak, M.S., Hightower, A.W., Vulule, J.M., Schoute, E., Kamau, L., et al. (2003). "Effect of Permethrin-treated bed nets on the spatial distribution of malaria vectors in Western Kenya." *American Journal of Tropical Medicine and Hygiene* 68(4 Suppl.), 115–120.

Giné X., Goldberg, J., Silverman, D., Yang, D. (2014). "Revising commitments: field evidence on the adjustment of prior choices." Washington D.C.: World Bank.

Giné X, Townsend R, Vickery J. (2009). "Forecasting when it matters: evidence from semi-arid India." World Bank Working Paper Washington, DC: World Bank.

Gourieroux, C., Monfort, A., Trognon, A. (1984). "Pseudo Maximum Likelihood Methods: applications to Poisson models." *Econometrica* 52: 701-720.

GSS, GHS, & ICF Macro (2009). "Ghana Statistical Service, Ghana Health Service, & ICF Macro." *Ghana Demographic and Health Survey 2008*. Accra, Ghana.

Guyatt, H. L., & Snow, R.W. (2002). "The cost of not treating bed nets." *Trends in Parasitology* 18(1): 12–16.

Halevy, Y. (2015). "Time consistency: stationarity and time invariance." *Econometrica* 83(1): 335-352.

Harmon, C., & Nolan, B. (2001). "Health insurance and health services utilization in Ireland." *Health Economics* 10(2): 135-145.

Heltberg, R. and Lund, N. (2009). "Shocks, coping, and outcomes for Pakistan's poor: health risks predominate." *Journal of Development Studies* 45(6): 889-910

Hill, Z., Arthur, P., Kendall, C., Kirkwood, B., & Adjei, E. (2003). "Recognizing childhood illness and their traditional explanations: exploring options for care-seeking interventions in the context of the IMCI strategy in rural Ghana." *Tropical Medicine & International Health* 8(7): 668-676.

Hoddinott, J. (2006). "Shocks and their consequences across and within households in rural Zimbabwe." *Journal of Development Studies* 42(2): 301-321

Howard, S.C., Omumbo, J., Nevill, C., Some, E.C., Donnely, C.A., & Snow, R.W. (2000). "Evidence for a mass community effect of insecticide-treated bed nets on the incidence of malaria on the Kenyan Coast." *Transactions of the Royal Society of Tropical Medicine and Hygiene* 94(4): 357–60.

Islam, A. and Maitra, P. (2012). "Health shocks and consumption smoothing in rural households: does microcredit have a role to play?" *Journal of Development Economics* 97(2): 232-243

Jehu-Appiah, C., Aryeetey, G., Spaan, E., de Hoop, T., Agyepong, I., & Baltussen, R. (2011). "Equity aspects of the National Health Insurance

Scheme in Ghana: who is enrolling, who is not and why?" *Social Science & Medicine* 72(2): 157-165.

Jones, A.M. (2011) "Models for health care", in Hendy, D. and Clements, M. (eds.) *Oxford Handbook of Economic Forecasting*, Oxford: Oxford University Press

Jowett, M., Contoyannis,P. and Vinh, N.D. (2003). "The impact of public voluntary health insurance on private health expenditure in Vietnam." *Social Science and Medicine* 56 (2): 333-342

Kaestner, R., & Carroll, A. (1997). "New estimates of the labour market effects of workers' compensation insurance." *Southern Economic Journal*, 63(3): 635-651.

Kenkel, D.S. (2000). "Prevention." In A.J. Culyer, & J.P. Newhouse (Eds.), *Handbook of Health Economics* (pp. 1675-1720). North-Holland: Elsevier.

Klein, R.E., Weller, S.C., Zeissig, R., Richards, F.O., & Ruebush, T.K. (1995). "Knowledge, beliefs and practices in relation to malaria transmission and vector control in Guatemala." *American Journal of Tropical Medicine & Hygiene* 52(2): 383-388.

Kleinjans, K.J., van Soest A. (2014). "Rounding, focal point answers and nonresponse to subjective probability questions." *Journal of Applied Econometrics* 29(4): 567-585

Klick, J., & Stratmann, T. (2007). "Diabetes treatments and moral hazard." *Journal of Law and Economics* 50(3): 519-538.

Koch, S., & Alaba, O. (2010). "On health insurance and household decisions: a treatment effect analysis." *Social Science & Medicine* 70(2): 175-182.

Kochar, A. (1995). "Explaining household vulnerability to idiosyncratic income shocks." *The American Economic Review* 85(2): 159-164

Kochar, A. (1999). "Smoothing consumption by smoothing income: hours-of-work response to idiosyncratic agricultural shocks in rural India." *The Review of Economics and Statistics* 81(1): 50-61

Kowalski, A.E. (2015). "What do longitudinal data on millions of hospital visits tell us about the value of public health insurance as a safety net for the young and privately insured?" NBER WP20887, Cambridge, MA: NBER

Lechner, M. (2001). "Identification and estimation of causal effects of multiple treatments under the conditional independence assumption." In M. Lechner, & F. Pfeiffer (Eds), *Econometric Evaluations of Active Labor Market Policies in Europe* (pp. 43-58). Heidelberg: Physica.

Leive, A. and Xu, K. (2008). "Coping with out-of-pocket health payments: empirical evidence from 15 African countries." *Bulletin of the World Health Organization* 86(11): 849-856

Leon, A.S. (2012). "The cost of incomplete consumption insurance against health shocks: evidence from Mexico." Available on http://paa2013.princeton.edu/papers/131594

Levine, D., Polimeni, R. And Ramage, I. (2014). "Insuring health or insuring wealth? an experimental evaluation of health insurance in rural Cambodia." IRLE Working Paper No.109-14. http://www.irle.berkeley.edu/workingpapers/109-14.pdf

Levy, H. (2002). "The economic consequences of being uninsured." Working Paper 12. ERIU

Lindelow, M. and Wagstaff, A. (2005). "Health shocks in China: are the poor and uninsured less protected?" World Bank Policy Research Working Paper 3740. World Bank.

Louis, J.P., LeGoff, G., Trebucq, A., Migliani, R., Louis, F.J., Robert, V., et al. (1992). "Feasibility of mosquito control using insecticide-impregnated bed nets in rural areas of Cameroon." *Annales de la Societe Belge de Medicine Tropicale* 72(3): 189-195.

Lu, C., Chin, B., Lewandowski, J.L., Basinga, P., Hirschhorn, L.R., Hill, K., Murray, M. and Binagwaho, A. (2012). "Towards universal health coverage: an evaluation of Rwanda's Mutuelles in its first eight years." *PLoS One* 7(6): e39282.

Manning, W.G., Mullahy, J. (2001). "Estimating log models: to transform or not to transform?" *Journal of Health Economics* 20(4): 461-494.

Manski, C.F. (2004). "Measuring expectations." *Econometrica* 72(5): 1329-1376

Mckenzie, D., Gibson, J. and Stillman, S. (2013). "A land of milk and honey with streets paved with gold: do emigrants have over-optimistic expectations about incomes abroad." *Journal of Development Economics* 102: 116-127

Mebratie, A. D., Sparrow, R.A., Alemu, G. and Bedi, A.S. (2013a). "Community-Based Health Insurance Schemes: a systematic review." ISS Working Paper Series/General Series. Vol. 568: ISS-EUR

Mebratie, A.D., Sparrow, R., Yilma, Z., Abebaw, D., Alemu, G. and Bedi, A. (2013b). "Impact of Ethiopian Pilot Community Based Heath Insurance Scheme on health care utilization: a household panel data analysis." *The Lancet,* 381: S92

Mebratie, A.D., Sparrow, R., Yilma, Z., Alemu, G. and Bedi, A. (2015). "Enrolment in Ethiopia's Community Based Health Insurance Scheme." *World Development,* 74: 58-76

Mensah, J., Oppong, J.R., and Schmidt, C.M. (2010). "Ghana's National Health Insurance Scheme in the context of the health MDGs: an empirical evaluation using propensity score matching." *Health Economics* 19(S1): 95-106.

Mohanan, M. (2013). "Causal effects of health shocks on consumption and debt: quasi-experimental evidence from bus accident injuries." *The Review of Economics and Statistics* 95(2): 673-681

Monheit, A.C., & Vistnes, J.P. (2008). "Health insurance enrolment decisions: preferences for coverage, worker sorting, and insurance take-up." *Inquiry* 45(2): 153-167.

Morduch, J. (1995). "Income smoothing and consumption smoothing." *Journal of Economic Perspectives* 9(3): 103-114

Nerlove, M. (1958). "Adaptive expectations and cobweb phenomena." *Quarterly Journal of Economics* 72(2): 227-240.

Nevill, C. G., Some, E.S., Mung'ala, V.O., Mutemi, W., New, L., Marsh et al. (1996). "Insecticide-treated bed nets reduce mortality and severe morbidity from malaria among children on the Kenyan Coast." *Tropical Medicine & International Health* 1(2): 139-146.

Newhouse, J.P. (1993). "*Free for all? Lessons from the RAND Health Insurance Experiment.*" Cambridge: Harvard University Press.

Newhouse, J. P., Manning, W. G., Keeler, E. B., and Sloss, E. M. (1989). "Adjusting capitation rates using objective health measures and prior utilization." *Health Care Financing Review* 10(3): 41-54.

Nguyet, N.T.N. and Mangyo, E. (2010). "Vulnerability of households to health shocks: an Indonesian study." *Bulletin of Indonesian Economic Studies* 46(2): 213-235

NHIA (2009). Ghana National Health Insurance Authority. *Annual Report 2009.* http://www.nhis.gov.gh/_Uploads/dbsAttachedFiles/1%281%29.pdf Retrieved January 2011.

Parmar, D., Souares, A., de Allegri, M., Savadogo, G., and Sauerborn, R. (2012). "Adverse selection in a Community-Based Health Insurance in rural Africa: Implications For Introducing Targeted Subsidies." *BMC Health Services Research* 12(1): 181

Phillips-Howard, P.A., Nahlen, B.L., Kolczak, M.S., Hightower, A.W., Ter Kuile, F.O., Alaii, J.A. et al. (2003). "Efficacy of Permethrin-treated bed nets in the prevention of mortality in young children in an area of high Perennial malaria transmission in Western Kenya." *American Journal of Tropical Medicine and Hygiene* 68(4 Suppl.): 23–29.

PMI (2010). President's Malaria Initiative. *Malaria Operational Plan – FY 2011 (Year 4): Ghana.* http://www.fightingmalaria.gov/countries/mops/fy11/ghana_mop-fy11.pdf Retrieved January 2011.

Population Census Commission, Federal Democratic Republic of Ethiopia (2008) "Summary and statistical report of the 2007 population and housing census." Addis Ababa, Ethiopia.

Preker, A.S. and Carrin, G. (2004). "Health financing for poor people: resource mobilization and risk sharing." World Bank, Washington DC.

Rosenbaum, P., & Rubin, D. (1983). "The central role of the propensity score in observational studies for causal effects." *Biometrika* 70(1): 41-55.

Rubin, D. (1974). "Estimating causal effects of treatments in randomized and non-randomized studies." *Journal of Educational Psychology* 66(5): 688-701.

Rubin, D. (1978). "Bayesian inference for causal effects: the role of randomization." *Annals of Statistics 6*(1): 34-58.

Rutstein, S.O. and Johnson, K. (2004). "DHS comparative reports 6: The DHS wealth index"

Santos, P. and Barrett, C. (2011). "Persistent poverty and informal credit." *Journal of Development Economics* 96(2): 337–47

Santos Silva, J.M.C., Tenreyro, S. (2006). "The log of gravity." *Review of Economics and Statistics* 88 (4): 641-658.

Santos Silva, J.M.C., Tenreyro, S. (2011). "Further simulation evidence on the performance of the poisson pseudo-maximum likelihood estimator." *Economics Letters* 112(2): 220-222.

Sapelli, C., & Vial, B. (2003). "Self-selection and moral hazard in Chilean health insurance." *Journal of Health Economics* 22(3): 459-476.

Sarpong, N., Loag, W., Fobil, J., Meyer, C.G., Adu-Sarkodie, Y., May, J. et al. (2010). "National Health Insurance coverage and socio-economic status in a rural district of Ghana." *Tropical Medicine & International Health* 15(2): 191-197.

Schultz, T.P and Tansel, A. (1997). "Wage and labor supply effects of illness in Cote d'ivoire and Ghana: instrumental variable estimates for days Disabled." *Journal of Development Economics* 53(2): 251-286

Sen, A. (1981). "*Poverty and famines: an essay on entitlement and deprivation*." Oxford. Oxford University Press.

Shapira G. (2013). "How subjective beliefs about HIV infection affect lifecycle fertility: evidence from rural Malawi." Policy Research Working Paper 6343, World Bank, Washington DC.

Shimeles, A. (2010). "Community Based Health Insurance Schemes in Africa: the case of Rwanda." GU Working Papers in Economics 463. Göteborg: Göteborg University.

Sindelar, J and Thomas, D. (1991). "Measurement of child health: maternal response bias." Economic Growth Center Discussion paper No.633, Yale University

Smith, V.H., & Goodwin, B.K. (1996). "Crop insurance, moral hazard and agricultural chemical use." *American Journal of Agricultural Economics* 78(2): 428-438.

Smith, K.V. and Sulzbach, S. (2008). "Community-Based Health Insurance and access to maternal health services: evidence from three West African countries." *Social Science & Medicine* 66(12): 2460-2473.

Sparrow, R., van de Poel, E., Hadiwidjaja, G., Yumna, A., Warda, N. and Suryahadi, A. (2014). "Coping with the economic consequences of ill health in Indonesia." *Health Economics* 23(6): 719-728.

Stewart, A., Ware, J., Brook, R. and Davies-Avery, A. (1990). "*Measurement of adult health status: physical health in terms of functional status*." Cambridge, MA: Harvard University Press.

Tarozzi, A., & Mahajan, A. (2011). "Time inconsistency, expectations and technology adoption: the case of insecticide treated nets." Economic Research Initiatives at Duke (ERID) Working Paper No. 105.

Townsend, R. (1994). "Risk and insurance in village India." *Econometrica* 62(3): 539-591

Trujillo, A.J., Vecino Ortiz, A.I., Ruiz Gómez, F., & Steinhardt, L.C. (2003). "Health insurance doesn't seem to discourage prevention among diabetes patients." *Health Affairs* 29(12): 2180-2188.

UN (2014). Data retrieved April 22, 2015, from Human Development Indicators Online (HDI) database.

USAID (2011, November). "Ethiopian Health Sector Financing Reform: Mid Term Project Evaluation Summary Report."

Van Bortel, W., Barutweanayo, M., Delacollette, C., & Coosemans, M. (1996). "Motivations to acquire impregnated mosquito nets in stable malaria zone in Burundi." *Tropical Medicine & International Health* 1(1): 71-80.

Van Doorslaer, E., O. O'Donnell et al (2007) "Catastrophic payments for health care in Asia." *Health_Economics*, 16 (11): 1159-1184.

Van Vliet, R. (1992). "Predictability of individual health care expenditures." *Journal of Risk and Insurance* 59(3): 443-460.

Wagstaff, A. (2007). "The economic consequences of health shocks: evidence from Vietnam." *Journal of Health Economics* 26(1): 82-100

Wagstaff, A. and Lindelow, M. (2010). "Are health shocks different? Evidence from a multi-shock survey in Laos." World Bank Policy Research Working Paper 5335. World Bank

Wagstaff, A., Lindelow, M., Jun, G., Ling, X. and Juncheng, Q. (2009). "Extending health insurance to the rural population: an impact evaluation of China's new cooperative medical scheme." *Journal of Health Economics* 28(1): 1-19.

Wagstaff, A. and Pradhan, M. (2005). "Health insurance impacts on health and nonmedical consumption in a developing country." Policy Working Paper Series 3563, The World Bank

Wang, H., Zhang, L., Yip, W. And Hsiao, W. (2006). "Adverse selection in a Voluntary Rural Mutual Health Care health insurance scheme in China." *Social Science and Medicine* 63 (5): 1236-1245.

World Bank (2013). Data retrieved April 22, 2015, from World Development Indicators Online (WDI) database

World Bank (2014). World Development Report 2014. Washington DC

WHO (2010). World Malaria Report 2010. Geneva

WHO and World Bank (2013). "Monitoring progress towards universal health coverage at country and global levels: a framework." Joint WHO and WBG Discussion Paper for Consultation

Xu, K., Evans, D., Kawabata, K., Zeramdini, R., Klavus, J., and Murray, C.. (2003). "Household catastrophic health expenditure: a multi-country analysis". *The Lancet* 326(9378): 111-117

Yilma, Z., Mebratie, A., Sparrow, R., Abebaw, D., Dekker, M., Alemu, G. and Bedi, A.S. (2014). "Coping with shocks in rural Ethiopia." *The Journal of Development Studies* 50(7): 1009-1024.

Yip, W., & Berman, P. (2001). "Targeted health insurance in a low income country and its impact on access and equity in access: Egypt's school health insurance." *Health Economics* 10(3): 207-220.

Zweifel, P., & Manning, G. (2000). "Moral hazard and consumer incentives in health care." In A.J. Cuyler, & J.P. Newhouse (Eds.), *Handbook of Health Economics* (pp. 410-459). North-Holland: Elsevier.

# Zelalem Yilma Debebe

## Education

| | |
|---|---|
| 2015 | PhD, Erasmus University Rotterdam, International Institute of Social Studies, The Netherlands (expected) |
| 2010 | Advanced Masters in International Development (Excellent thesis), Radboud University Nijmegen, The Netherlands |
| 2009 | MA (major) in Economics of Development (with Distinction, CGPA 91%), Erasmus University Rotterdam, International Institute of Social Studies, The Netherlands |
| 2006 | BA in Economics (with Great Distinction, CGPA 3.94/4.00), Jimma University, Ethiopia |

## Awards, Grants and Certificates

| | |
|---|---|
| 2015 | Young Professionals Program, The World Bank |
| 2014 | Young African Fellowship Program, The World Bank |
| 2012 | Health Financing and Evaluation of Health Policies Training, Erasmus University Rotterdam, International Institute of Social Studies |
| 2010 | NWO-WOTRO full grant for a PhD research |
| 2009 | 'Best three MA research papers' of The International Institute of Social Studies, Erasmus University Rotterdam |
| 2008 | The prestigious HSP Huygens Scholarship for MA study and research |
| 2007 | Advanced Research Methodology Training, Fulbright Senior Scholarship |
| 2006 | 'Best three students' of the department of economics, Jimma University |

**Work Experience**

| | |
|---|---|
| Sept. 2015- present | Young Professional, World Bank, Washington DC |
| Sept. 2014- June 2015 | World Bank Research Fellow, World Bank, Washington DC |
| Feb. 2011- present | PhD researcher, Erasmus University Rotterdam, The Hague |
| Jan. 2010- Dec. 2010 | Junior Researcher, Radboud University Nijmegen, Nijmegen |
| Aug. 2006- Aug. 2008 | Instructor and Researcher, Jimma University, Jimma |

**Teaching Experience (Selected)**

Quantitate methods for economists I and II
Research methods for economists
Micro-economics I and II
Statistics for economists

**Professional Activities**

| | |
|---|---|
| 2014/5 | Reviewer for academic journals: Geneva Papers on Risk and Insurance; Journal of Public Health; BMC Public Health |
| 2012 | Reviewer for 3ie impact evaluation fund proposals |
| 2012 | External examiner for MSc thesis in economics, Jimma University |
| 2012 | External examiner for MSc thesis in economics, Bahirdar University |
| 2012 | Training the academic staff of Bahirdar University on advanced quantitative research methods |

**Published Papers**

Yilma Z., Mebratie, A., Sparrow, R., Dekker, M., Alemu, G., and Bedi, A.S. (2015). Impact of Ethiopia's Community Based Health Insurance on household economic welfare. *World Bank Economic Review* doi:10.1093/wber/lhv009

Mebratie, A., Sparrow, R., Yilma, Z., Alemu, G. and Bedi, A.S. (2015). Enrolment in Ethiopia's Community Based Health Insurance Scheme. *World Development* 74: 58-76

Mebratie, A.D., Sparrow, R., Yilma, Z., Alemu, G. and Bedi, A.S. (2015). Dropping out of Ethiopia's Community Based Health Insurance Scheme. *Health Policy and Planning* doi: 10.1093/heapol/czu142

Yilma Z., Mebratie, A.D., Sparrow, R., Abebaw, D., Dekker, M., Alemu, G., and Bedi, A.S. (2014). Coping with shocks in rural Ethiopia. *Journal of Development Studies*, 50(7): 1009-1024

Mebratie, A.D., van de Poel, E., Yilma, Z., Abebaw, D., Alemu, G. and Bedi, A.S. (2014). Healthcare-seeking behaviour in rural Ethiopia: evidence from clinical vignettes. *BMJ Open, 4:1-12*

Mebratie, A.D., Sparrow, R., Yilma, Z., Abebaw, D., Alemu, G. and Bedi, A.S. (2013). The impact of Ethiopia's pilot Community Based Health Insurance scheme on healthcare utilization and cost of care. *The Lancet* 381, supplement 2: page S92 (abstract only). Full version available as ISS Working Paper No. 593 (2014)

Yilma Z., van Kempen L., and de Hoop T. (2012). A perverse 'net' effect? Health insurance and ex-ante moral hazard in Ghana. *Social Science and Medicine*, 75 (1): 138-147

**Under Review and completed**

Yilma Z., Mebratie, A., Sparrow, R., Dekker, M., Alemu, G., and Bedi, A.S. "Channels of impoverishment due to ill-health in rural Ethiopia". Also available as ISS Working Paper 592 (2014)

Yilma Z., O'Donnell, O., Mebratie, A.D., Alemu, G., and Bedi, A.S. "Subjective expectations of medical expenditures and insurance in rural Ethiopia".

Mebratie, A.D., Sparrow, R., Yilma, Z., Abebaw, D., Alemu, G. and Bedi, A.S. (2013). The impact of Ethiopia's pilot Community Based Health Insurance scheme on healthcare utilization and cost of care.

Debebe, Z.Y. (2010). Child labor, agricultural shocks and labor sharing in rural Ethiopia. ISS Working Papers- General Series 491, International Institute of Social Studies, Erasmus University Rotterdam, The Hague

**Policy Briefs**

Yilma Z., Mebratie, A., Sparrow, R., Dekker, M., Alemu, G., and Bedi, A.S. (2015). The impact of Ethiopia's Community Based Health Insurance on household economic welfare: a policy brief. *African Studies Centre Info sheet 23*

Yilma Z., Mebratie, A., Sparrow, R., Dekker, M., Alemu, G., and Bedi, A.S. (2015). Impact of Ethiopia's Community Based Health Insurance on household economic welfare: a policy brief. *OSSREA Bulletin Vol. XII, No.1*

Mebratie, A.D., van de Poel, E., Yilma, Z., Abebaw, D., Alemu, G. and Bedi, A.S. (2015). Self-reported healthcare seeking behaviour in rural Ethiopia: evidence from clinical vignettes. A policy brief. *OSSREA Bulletin Vol. XII, No.1*

Yilma Z., Mebratie, A.D., Sparrow, R., Abebaw, D., Dekker, M., Alemu, G., and Bedi, A.S. (2014). Shocks and coping strategies in rural Ethiopia: a policy brief. *OSSREA Bulletin Vol. XI, No.1*

Yilma Z., Mebratie, A.D., Sparrow, R., Abebaw, D., Dekker, M., Alemu, G., and Bedi, A.S. (2014). Shocks and coping strategies in rural Ethiopia: a policy brief. *African Studies Centre Info sheet 22*

**Presentations (Academic)**

2014 Annual Bank Conference on Africa (ABCA), Paris School of Economics and The World Bank, (Paris, France)

2014 Nordic Conference on Development Economics, UNU-WIDER, (Helsinki, Finland)

2014 Annual Bank Conference in Development Economics (ABCDE), The World Bank, (Washington DC, USA)

2013 The 12th European Development Research Network (EUDN) PhD workshop, The Graduate Institute-Geneva, (Geneva, Switzerland)

2013 PhD Conference on International Development, University of East Anglia, (Norwich, England)

2011 The 10th LAGV Conference in Public Economics, Institute for Public Economics, (Marseille, France)

2011 DIAL Development Conference, University of Paris-Dauphine and the French Institute of Research for Development, (Paris, France)

2011 Research Colloquium, Institute of Development Studies, Ruhr University, (Bochum, Germany)

2010 NISCO Research Day, Radboud University Nijmegen, (Nijmegen, The Netherlands)

In an attempt to achieve the goal of Universal Health Coverage by 2030 and to break the bridge between ill-health and impoverishment, several developing countries are undergoing various healthcare financing reforms. One of these is the introduction of health insurance. The aim of this thesis is to provide evidence regarding the need for health insurance in rural Ethiopia and to investigate the effectiveness and potential problems of (pilot) health insurance schemes in Sub-Saharan Africa.

Zelalem Yilma currently holds the position of a Young Professional at the World Bank, Washington DC. Before his new appointment, he was a PhD researcher at Erasmus University Rotterdam, The Netherlands. In collaboration with other researchers he has published in international peer reviewed journals such as *The World Bank Economic Review, World Development, Journal of Development Studies, Social Science and Medicine, Health Policy and Planning, and BMJ Open.* His research interest lies in the area of applied microeconomics. He can be reached at zelexyilma@gmail.com.