The High 5

The Impacts of Community-Based Health Insurance on Poverty Reduction

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Abstract

Every year, millions of people suffer from financial catastrophe due to out-of-pocket healthcare payments and most of them are pushed into poverty. This study investigates the impacts of community-based health insurance schemes on health-related financial shocks and poverty, using a nationally representative household survey data from Rwanda. We address issues of selection bias in health insurance enrollment, heterogeneity in treatment effects and non-normality in the outcome variables using Extended Two-Part Model within a Bayesian estimation framework. We find that community-based health insurance schemes reduce the incidence of catastrophic healthcare spending by about 20 percentage points. We also finding that community-based health insurance schemes reduce the headcount poverty rates and the poverty gap due to out-of-pocket healthcare payments by about 8 percentage points and by about 3 USD in 2000 prices, respectively. The estimated treatment effects are however heterogeneous across households.

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Community-Based Health Insurance and Poverty

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1. Introduction

Health shocks, such as illness and disabilities are the most important causes of extreme poverty and their persistence in most developing countries (Fafchamps, 1999). Health shocks present considerable stress on the financial wellbeing of families, often pushing households into poverty and the poor further into destitution. According to the World Health Organization (WHO), every year about 150 million people suffer from financial catastrophe due to out-of-pocket healthcare payments and 100 million of them are pushed into poverty (WHO, 2010). In recent years, however, many low- and middle-income countries have adopted various forms of risk pooling mechanisms to fill the gap in their healthcare financing systems. Expansion of traditional Social Health Insurance (SHI) programs and adoption of Community-Based Health Insurance (CBHI) schemes, mainly for people in the informal and subsistence agricultural sectors, are the most common national insurance programs in developing countries (Acharya, 2010).

Rwanda is one of the most successful countries in Africa to implement the CBHI schemes as a major part of its national healthcare financing system. Introduced in 1999 as a pilot in three districts, locally known as *Mutuelle de santé*, the program was formally implemented at the national level in 2004. Since the nationwide implementation started, coverage expanded from that of 36% of the population in 2006 to more than 86% in recent years. The CBHI schemes are subsidized, with subsidies covering up to 50% of the national fund pool. Between 2004 and 2007, enrollment was on a household basis where a household with up to seven family members paying premiums ranging from 2,500 to 11,000 RwF per year and co-pays of up to 150 RwF for services provided at health clinics and up to 50% of the cost at hospitals (Lu et al., 2012). Later in 2007, the national CBHI policy was revised to make enrollment on an individual basis, each member paying a flat premium of 1,000 RwF per year and a co-pay of 200 RwF at health clinics and 10% of hospital cost. The benefits package includes comprehensive preventive and curative services and essential drugs provided at the health centers and the referral hospitals.

Evidence shows that the CBHI program has largely succeeded in Rwanda in terms of increasing healthcare utilization rates, reducing out-of-pocket healthcare spending, and reducing the risk of financial catastrophe (Shimeles, 2010; Lu et al., 2012; Woldemichael et al. 2015). However, the impacts of the CBHI program in reducing health-related poverty, particularly, the extent to which the program reduced the risk of falling into poverty and the depth of poverty (the poverty gap) due to healthcare payments is not well documented. In the literature, healthcare spending is considered catastrophic if it exceeds a certain proportion of total or non-food consumption expenditure (Berki, 1986; Wyszewianski, 1986a, 1986b). The idea is that paying for healthcare should not reduce households' consumption of necessities below acceptable thresholds (Xu et al. 2003; Wagstaff and van Doorslaer, 2003). There is no single best threshold for the acceptable level of healthcare spending as the share of consumption expenditure, however spending on health care more than 30 to 40 percent of non-food consumption expenditure is considered as catastrophic. When out-of-pocket healthcare spending pushes non-health household consumption the below poverty line, it is considered impoverishing.

In this paper, we investigate the impacts of the Rwandan CBHI program on key measures of health-related financial wellbeing and poverty. We estimate the causal effects the health insurance program on the incidence of catastrophic healthcare spending, headcount poverty, and poverty gap caused by out-of-pocket healthcare payments. Our study uses a nationally representative household survey data from Rwanda collected in three rounds, between 2000 and 2010. One of the main empirical challenges we face in estimating treatment effects using such nonrandomized datasets is endogeneity in enrollment. The ideal approach to handle endogeneity would be to conduct a randomized control study where households are randomly assigned to CBHI schemes. In the absence of such data, however, one needs to employ statistical tools to adjust for biases arising from self-selection. Because households who self-select into or out of the CBHI schemes could exhibit systematic differences in their preferences toward insurance, risk attitude, underlying health conditions, and other factors which are also correlated with the outcome variables. If self-selection is ignored, the estimated treatment effects therefore would be biased upwards or downwards depending on the direction and the magnitude of correlation. In addition to the problem of endogeneity largely due to omitted variable bias, heterogeneity in treatment effects and non-normality in healthcare expenditure variables pose econometric challenges, but largely ignored in the literature.

We address endogeneity on both observable and unobservable factors by jointly modeling the decision to enroll in CBHI schemes and the outcome variables, allowing the corresponding error terms to be correlated. We use a bivariate probit model to estimate the impacts of CBHI on the incidence of catastrophic spending and headcount poverty. In order to model the impacts on poverty gap, which is positive and continuous outcome with a mass at zero, we use Extended Two-Part Model (ETPM) proposed by Deb et al. (2006). The ETPM addresses both endogeneity and the problem of high proportion of zero healthcare expenditure in our data. Such truncated distribution in out-of-pocket expenditure data with mass at zero is pervasive among the poor. This is due to “corner solution” in the choice problem or health goods and services are not in the choice sets of some households. Heterogeneity in treatment effects is another important issue that we give special attention to in this paper. The empirical models handle heterogeneity by estimating treatment effects at the individual level and present the whole distribution. The models are estimated using a Bayesian estimation framework with Markov Chain Monte Carlo (MCMC) simulation techniques.

We find that the CBHI program reduces the incidence of financial catastrophe by about 20 percentage points. It also reduces the probability of falling below extreme poverty due to out-of-pocket healthcare payments by about 8 percentage points and the depth of poverty by 1,127 Rwandan Franc (RwF)[2], which is about 51 percent reduction in the cost of eliminating extreme poverty caused by out-of-pocket healthcare payments. The reduction in the depth of poverty is even larger and statistically significant for moderate poverty line of $2.00 per day. We also find significant self-selection in the CBHI enrollment on observed and unobserved factors. Ignoring self-selection, therefore, considerably biases the magnitude and the direction of estimated treatment effects. In addition to our main estimation model using Bayesian methods, we run several estimations using classical econometric models and establish that the findings are consistent and robust.

The key message from our study is that, in Rwanda, the CBHI program not only increases the utilization of modern healthcare services but also serves as an important tool to reducing catastrophic financial risks and reducing poverty. The caveat in our study is that the estimated treatment effects are based on current levels of consumption and do not reflect the long-term welfare impacts of the CBHI coverage. Financial catastrophe and impoverishment due to payments for healthcare could perpetuate well beyond the current period. Hence, in terms of welfare impacts, the estimated treatment effects of the CBHI in our study should be considered as lower bounds.

[2] This is approximately, 2.89 USD in 2000 prices.

The rest of the paper is organized as follows. Section (2) describes the data, Section (3) presents the econometric model, Section (4) discusses the results, and Section (5) concludes the paper.

2. The Data and Descriptive Analysis

The data comes from three rounds of the Rwandan Household Living Standard Survey collected over 10 year period, in 2000/2001, 2005/2006, and 2010/2011. It is a nationally representative survey, gathering information on household demographics, socio-economic characteristics, health, health insurance status, incomes, wealth, etc. as well as area-level characteristics. Depending on the frequency of purchase, information on expenditures is collected at the household level over different recall periods. Membership in the CBHI, on the other hand, is recorded at the individual level. We consider households as enrolled if at least one family member is enrolled, otherwise we consider the household not enrolled.

The data shows that in two years since the formal implementation of the program, about 42% of the households were enrolled in 2005/2006. Subsequently, enrollment increased to 76% in 2010. A small proportion of households—9% in 2005 and 5% in 2010—have health insurance coverage from other sources such as the Rwandan Medical Insurance Scheme (RAMA) for public employees and health insurance for the military (MMI). There are also few households in the survey who reported to have insurance coverage from private health insurance companies. Because our focus is to estimate the impacts of CBHI, we exclude household with formal health insurance. This leaves us with a pooled sample size of 26,193 households (i.e., 6,391 from the 2000/2001, 6,253 from the 2005/2006, and 13,549 from the 2010/2011 surveys).

The first outcome variable is the incidence of catastrophic spending. In the literature, healthcare spending is considered catastrophic if the share in total or non-food consumption expenditure exceeds a certain threshold. The concept was first introduced in the literature by Berki (1986) and Wyszewianski (1986a, 1986b) and later popularized in the context of low-income counties by researchers at the World Bank (Wagstaff and van Doorslaer, 2003) and WHO (Xu et al. 2003; Xu et al. 2007). However, there is no single best threshold in the literature to determine catastrophic healthcare spending where studies use different ad hoc thresholds depending on the context. For instance, most WHO studies consider healthcare spending catastrophic if it exceeds 40% of non-food consumption expenditure (Xu et al., 2007; 2010). In this study, we use three different thresholds: $z_c = 20\%$, $z_c = 30\%$, and $z_c = 40\%$ as the share of non-food consumption spending. Healthcare spending as a share of non-food consumption is used in the literature because, non-food consumption measures households' ability to pay.

The other outcome variables are the headcount poverty and the poverty gap. Under the condition that total household resources are fixed and healthcare spending is nondiscretionary, the difference between pre – and post – healthcare payment poverty estimates are considered the result of out-of-pocket healthcare payment (Wagstaff and van Doorslaer, 2003; O'Donnell et al., 2008). Of course, this approach does not capture the total effect of illness on poverty as paying for healthcare through borrowing, intertemporal transfers or forgoing care all together are not fully captured through out-of-pocket spending and could have long-term repercussions on poverty. The notion is that spending on healthcare should not come at the expense of sever decline in spending on necessities, such as food consumption (O'Donnell et al, 2008). The consensus in the healthcare financing and equity literature, therefore, is that poverty measures should take healthcare payments into account.

One of the issues in assessing poverty, if it is measured on the basis of consumption expenditure, is how to adjust the poverty line for pre- and post- healthcare payment expenditures. The common practice in the literature is that if the poverty line is strict enough to reflect spending on necessities, there is no need for downward adjustments (O'Donnell et al, 2008). For this reason, we use absolute extreme poverty line of $\$1.00$ per day which is converted into real values using the 2000 price and exchange rate of USD 1.00 = 389.70 RwF, i.e., a real poverty line of 142,241 RwF (i.e. $z_p = 1.00 \times 389.70 \times 365$) per year.

A household is considered poor if the per capita consumption expenditure is below the poverty line. Let x_i^{gross} and x_i^{net} denote consumption expenditure, gross and net of healthcare payments, respectively. Then, we calculate the pre – and post – healthcare payment incidence of poverty for household i as $p_i^{gross} = 1\left[x_i^{gross} < z_p\right]$ and $p_i^{net} = 1\left[x_i^{net} < z_p\right]$. The difference between p_i^{gross} and p_i^{net} is attributed to healthcare payments, i.e., $p_i^{\Delta} = p_i^{net} - p_i^{gross} = \{0,1\}$, where the value of 1 indicates whether or not household i is pushed below the poverty line due to healthcare payments. Similarly, we calculate the poverty gap, gross and net of healthcare payments, as $g_i^{gross} = p_i^{gross}\left[z_p - x_i^{gross}\right]$ and $g_i^{net} = p_i^{net}\left[z_p - x_i^{net}\right]$ on the basis of per capita consumption expenditure, gross and net of healthcare payments, respectively. Again, the difference between the two measures of the poverty gap $g_i^{\Delta} = g_i^{net} - g_i^{gross} = [0, \infty)$ is attributable to healthcare payments. The poverty gap measures how far households are below the poverty line or the amount of income or consumption shortfall relative to the poverty line (Ravallion, 1998).

Table (1) presents a summary of the outcome variables. The data shows that the share of healthcare payment in total expenditure has considerably decreased over the years. For instance, the share of healthcare expenditure in total per capita consumption expenditure has decreased from that of 4.4% in 2000/2001 to 1.4% and 2.1% in 2010/2011 for the uninsured and the insured, respectively. Similarly, the share of healthcare spending in non-food expenditure has considerably decreased from approximately 14% to just 6% and 8.1% for the uninsured and insured, respectively. The table also shows the incidence of catastrophic spending and poverty measures before and after healthcare payments are made. Overall, the incidence of incurring catastrophic medical spending is higher for the uninsured households as 13.3% of them spending more than 30% of non-food expenditure on healthcare. However, only 4.8% of households enrolled in CBHI incur healthcare spending more than 30% of their non-food expenditure. Although at different rates, the overall incidence of catastrophic spending due to out-of-pocket payments has decreased over time.

As shown in Figure (1), compared to the insured households, the proportion of households with catastrophic spending is higher among the uninsured. This holds irrespective of their rank in the income distribution. The figure also shows that regardless of insurance status, households at the bottom decile of income have a higher risk of financial catastrophe due to healthcare payments. Using $1.00 per day poverty line, in 2005, the headcount poverty due to healthcare payments was 1.3% for the uninsured and 0.8% for the insured, whereas in 2010, this figure was about 1.1% and 1.5% for the uninsured and the insured households, respectively. In 2010, the insured households did not fare well in terms of health-related poverty measures which could reflect increased CBHI enrollment in which households who were at the margin or near the poverty line.

Table (1): Summary of outcome variables

	Whole sample				Uninsured			CBHI		
	2000	2005	2010	Pooled	2005	2010	Pooled	2005	2010	Pooled
Share of Healthcare expenditure										
Total Consumption	4.4%	2.8%	1.9%	2.7%	3.4%	1.4%	3.4%	2.0%	2.1%	2.1%
Non-food	13.7%	8.8%	7.6%	9.4%	10.7%	6.0%	11.0%	6.4%	8.1%	7.7%
Catastrophic Spending										
Threshold: 20%	24.9%	15.5%	8.8%	14.3%	19.5%	8.2%	19.1%	10.4%	9.0%	9.2%
Threshold: 30%	19.0%	9.3%	4.6%	9.2%	12.3%	4.2%	13.3%	5.3%	4.7%	4.8%
Threshold: 40%	14.3%	5.6%	2.9%	6.3%	7.6%	2.7%	9.4%	3.0%	2.9%	2.9%
Headcount Poverty and Poverty Gap										
Headcount: Pre-payment	62.9%	61.0%	52.0%	56.8%	62.6%	62.0%	62.5%	59.1%	48.9%	51.0%
Headcount: Post-payment	65.2%	62.1%	53.4%	58.3%	63.9%	63.1%	64.2%	59.9%	50.4%	52.4%
Poverty Gap: Pre-payment (RwF)	65,489	61,307	50,571	32,583	65,332	55,709	39,147	55,858	48,585	25,668
	(33,490)	(32,348)	(29,834)	(37,361)	(32,141)	(30,491)	(40,016)	(31,834)	(29,339)	(33,115)
Poverty Gap: Post-payment (RwF)	68,590	63,417	52,097	34,023	67,810	56,735	40,986	57,470	50,304	26,718
	(32,570)	(31,901)	(29,572)	(37,907)	(31,523)	(30,264)	(40,485)	(31,453)	(29,106)	(33,614)
Poverty Differences (Pre-payment – Post-payment)										
Headcount	2.3%	1.1%	1.4%	1.5%	1.3%	1.1%	1.7%	0.8%	1.5%	1.3%
Poverty gap (RwF)	3,101	2,110	1,526	1,440	2,478	1,026	1,839	1,612	1,719	1,049
	(7,339)	(4,618)	(3,143)	(5,010)	(5,199)	(2,561)	(5,954)	(3,632)	(3,320)	(3,808)
Normalized poverty gap	2.2%	1.5%	1.1%	1.0%	1.7%	0.7%	1.3%	1.1%	1.2%	0.7%
	(0.05)	(0.03)	(0.02)	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)	(0.02)	(0.03)
No. of obs.	6,391	6,253	13,549	26,193	3,508	3,167	13,066	2,745	10,382	13,127

[#] International poverty line: USD 1.00/day = RwF 365.9/day in 2000 Forex and Prices. All RwF values are in 2000 prices. Standard deviations in bracket.

Figure (1): Percentage of households with catastrophic healthcare spending by CBHI status and income decile (40% threshold)

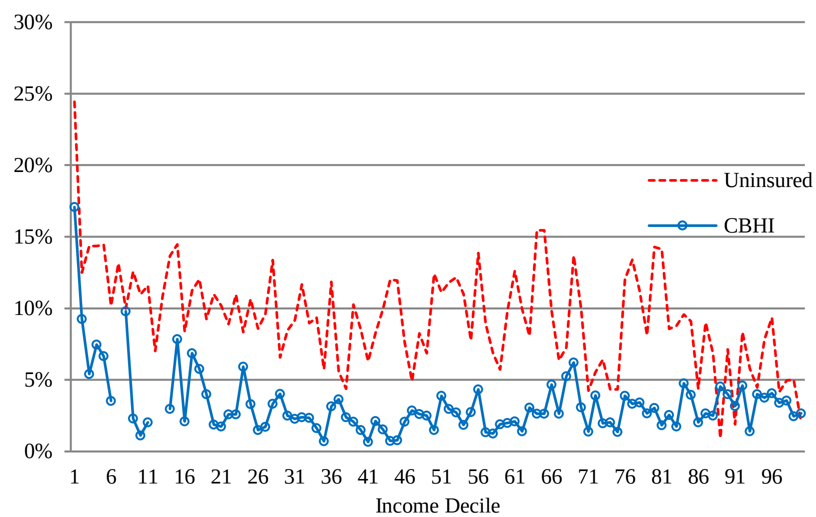
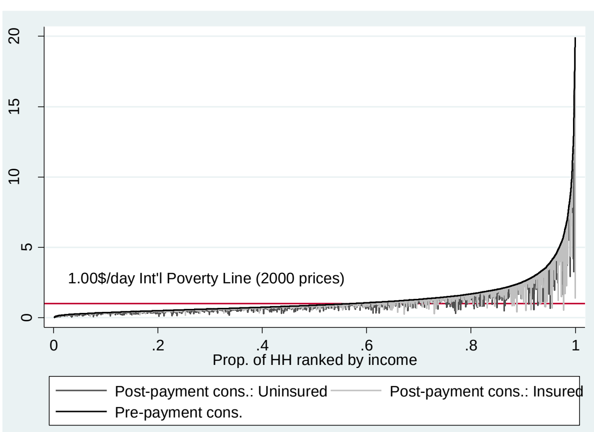


Figure (2a) shows the impoverishing impact of healthcare payment in Pen's "pared of giants and few dwarfs" for pre–healthcare payments (dark smooth line) and post–healthcare payments (gray line) consumption expenditures and the poverty line. The drop lines represent the amount of out-of-pocket payments for each household. The amount of out-of-pocket payment among the poor is lower than those in the top income distribution, highlighting the fact that poor households spend lower amount on healthcare or forego healthcare altogether hence zero payment. Although the magnitude becomes smaller for the extreme poor, out-of-pocket payment also pushes some non-poor households below poverty and the poor further into poverty. This is suggestive that some households in the middle- and top-income distribution must pay for healthcare even if it impoverishes them.

Similarly, Figure (2b) plots the poverty gap before and after paying for healthcare. Poverty gap is generally higher for the poorest of the poor, with a gap reaching up to 120,000 RwF for households at the bottom of the ranking. Clearly, higher out-of-pocket expenditure increases this gap and more importantly the magnitude of the gap varies by consumption level in which the very poor spend a lower amount on healthcare.

Figure (2): Impoverishing Impact of Out-of-Pocket Healthcare Payments by CBHI Status

2a) Jan Pen's "pared of dwarfs and a few giants"



2b) Poverty gap

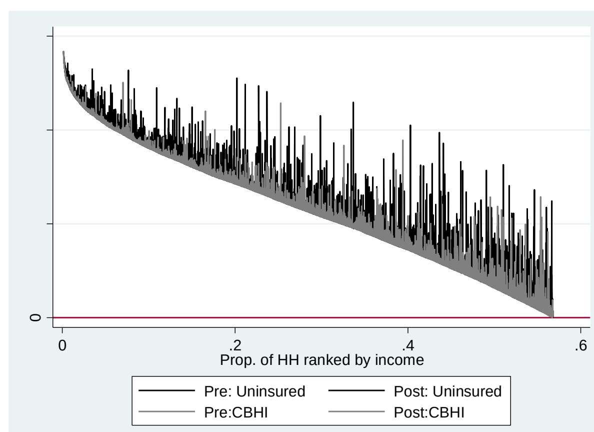


Table (2) presents descriptive statistics of key variables which are included in our regression analysis. These variables include household demographics and health characteristics such as age, household size, mean age in the household, sex and marital status of the head. The analysis also controls for health status and health behavior by including the number of individuals in the household who reported illness in the past two weeks, purchase of alcoholic drinks and cigarettes/tobacco. As a proxy for income, we also include household consumption quartiles. The wealth quartile is obtained from wealth index calculated using principal component analysis on the number of agricultural equipment, livestock, household durables, dwelling characteristics, and size of land owned by the household. We include year and 29 district dummies to capture temporal and spatial variations.

Table (2): Descriptive Statistics of Control Variables

		2005/2006		2010/2011	
	2000/2001	Uninsured	CBHI	Uninsured	CBHI
Head: Age	43.78	43.36	45.16	44.30	45.65
	(15.07)	(15.66)	(15.10)	(16.11)	(15.98)
Household size	5.01	4.69	5.31	4.43	4.83
	(2.34)	(2.27)	(2.30)	(2.08)	(2.17)
Mean Age in the household	22.79	23.48	23.10	24.79	24.63
	(10.59)	(11.37)	(10.27)	(13.45)	(11.52)
Head: Male	68%	69%	74%	69%	72%
Head: Married	18%	46%	60%	46%	57%
No. of individuals w/ illnesses	1.25	0.99	0.95	0.84	0.83
	(1.30)	(1.18)	(1.12)	(1.08)	(1.04)
Alcohol Use	42%	38%	41%	30%	31%
Cigarette Use	20%	21%	19%	25%	17%
Cons. expenditure: 1st Quartile	25%	32%	19%	36%	23%
Cons. expenditure: 2nd Quartile	25%	26%	27%	29%	25%
Cons. expenditure: 3rd Quartile	25%	23%	29%	23%	27%
Cons. expenditure: 4th Quartile	25%	19%	25%	12%	25%
Wealth index: 1st Quartile	25%	33%	19%	42%	22%
Wealth index: 2nd Quartile	25%	27%	25%	29%	25%
Wealth index: 3rd Quartile	25%	23%	30%	20%	28%
Wealth index: 4th Quartile	25%	17%	26%	9%	26%
Head's educ.: Primary	25%	57%	60%	63%	63%
Head's educ.: Secondary/Vocational/Tertiary	3%	8%	10%	5%	8%
Head's educ.: No education	71%	35%	30%	32%	28%
# of wage earners	0.54	0.92	0.84	1.76	1.43
	(0.87)	(1.02)	(1.03)	(1.45)	(1.41)
Urban	23%	24%	15%	12%	14%
Microfinance	14.5%	28.3%	41.7%	11.9%	19.7%
Involuntarily Relocated	2.0%	9.0%	7.1%	11.9%	11.0%
No. of households	6,391	3,508	2,745	3,167	10,382

3. Econometric Strategy

Our goal is to estimate the causal impacts of the CBHI on the incidence of catastrophic healthcare spending, the headcount poverty, and the poverty gap addressing endogeneity and heterogeneity in treatment effect. The treatment variable is binary indicating membership in the CBHI schemes and the outcome variables are the incidence of catastrophic spending, the headcount poverty, and the poverty gap. While the incidence of catastrophic spending and the headcount poverty indicators are binary, the poverty gap is censored continuous variable with a mass at zero (see Figure (B.1) in Appendix B). We estimate (i) binary treatment and binary outcome and (ii) binary treatment and censored continuous outcome model. These models address the issue of endogeneity by modeling household CBHI enrollment decisions jointly with the outcome variables. The models are laid out as follows:

Model (i): *Binary treatment and binary outcome model*. Let $T_i \in \{0,1\}$ denotes the treatment variable indicating CBHI enrollment and $d_i \in \{0,1\}$ denotes binary outcome variable. Then, the treatment effect model can be written in terms of latent variables as

$$T_i^* = \beta^T w_i \qquad\qquad + \varepsilon_i^T \qquad\qquad (1a)$$

$$d_i^* = \beta^d x_i + \gamma^d T_i + \varepsilon_i^d, \qquad\qquad (1b)$$

where $T_i = 1(T_i^* > 0)$, $d_i = 1(d_i^* > 0)$, $1(\cdot)$ is indicator operator, $\{T_i^*, d_i^*\}$ are the latent variables, γ^d is the treatment effect parameter, $\{\beta^T,\ \beta^d\}$ are vectors of slope parameters to be estimated, and $\{\varepsilon_i^T, \varepsilon_i^d\}$ are the error terms, and $w_i = [x_i\ z_i]$ is a vector of covariates in the selection equation, z_i is a vector of exogenous variables excluded from x_i. In this model, we assume that the error terms are jointly and normally distributed as $\varepsilon_i \sim n\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}1 & \sigma_{Td}\\ \sigma_{Td} & 1\end{bmatrix}\right)$, where $\varepsilon_i = [\varepsilon_i^T, \varepsilon_i^d]$, and σ_{Td} is the covariance term capturing selection on unobservables. For the purpose of identification in the probit model, the two diagonal elements are restricted to ones.

Model (ii): *Binary treatment and censored continuous outcome model*. In this case, the treatment variable is binary, and the outcome variable denoted by g_i^{Δ} is the poverty gap due to out-of-pocket healthcare payments. The poverty gap is censored with a mass at zero because the poverty gap is zero for non-poor households and a large proportion of households near the poverty line spend zero amount and hence the difference in poverty gap due to out-of-pocket healthcare payments is zero. For such non-normally distributed outcome variable, the ETPM proposed by Deb et al. (2006) is suitable, which is a mixture model with a binary specification for the zero part and linear for the continuous part. Let $h_i = \{0,1\}$ indicates whether the poverty gap is zero or not, then the expected poverty gap due to healthcare payment is given by

$$E\left[g_i^{\Delta} | x_i, T_i, \Theta\right] = \Pr(h_i = 1 | x_i, T_i, \Theta)\, E\left[g_i^{\Delta} | h_i = 1, x_i, T_i, \Theta\right], \tag{2}$$

where Θ is a vector of model parameters, x_i is a vector of covariates, $Pr(h_i = 1|x_i, T_i, \Theta)$ is the probability of a positive poverty gap, and $E\left[g_i^{\Delta}|h_i = 1, x_i, T_i, \Theta\right]$ is the expected conditional poverty gap. The ETPM handles endogeneity by jointly estimating the decision to enroll in the CBHI schemes, the probability that the poverty gap is positive, and the magnitude of the poverty gap.

The treatment effects for each individual is given by

$$TE_i|x = E_\theta[\Pr(d_i = 1|T_i = 1, x; \theta) - \Pr(d_i = 1|T_i = 0, x; \theta)] \tag{3}$$

for binary outcomes and

$$TE_i|x = E_\theta\left[g_i^{\Delta}|T_i = 1, x_i; \theta\right] - E_\theta\left[g_i^{\Delta}|T_i = 0, x_i; \theta\right], \tag{4}$$

for continuous censored outcomes, where E_θ is the expectation operator over the model parameters, $\Pr(d_i = 1|T_i, x; \theta) = \Phi\left(\beta^h x_i + \gamma^h T_i + \sigma_{dh}(T_i^* - \beta^T w_i)\right)$, and $E\left[g_i^{\Delta}|T_i, x_i; \theta\right] = \Phi\left(\beta^h x_i + \gamma^h T_i + \sigma_{Th}(T_i^* - \beta^T w_i)\right) \times \exp\left\{\beta^g x_i + \gamma^g T_i + \sigma_{Tg}(T_i^* - \beta^T w_i) + \frac{1}{2}\sigma_g^2\right\}$.

Then, the estimated treatment effect $\widehat{TE_\iota}(x_i)$ is calculated through Monte Carlo integration over the post-convergence parameters obtained from the MCMC iterations as

$$\widehat{TE_\iota}(x) = E_\theta[iTE(X; \theta)] \approx \frac{1}{R}\sum_{r=1}^{R} iTE\left(X; \tilde{\theta}_R\right), \tag{5}$$

where $\tilde{\theta}_R$ is a vector of post-convergence parameters. The calculated $\widehat{TE_\iota}(x)$ gives us the whole distribution of treatment effects from which one can obtain the usual summary statistics such as

Average Treatment Effects$\left(ATE = \frac{1}{N}\sum_{i=1}^{N}\widehat{TE_i}\right)$, Average Treatment Effects on the Treated $\left(ATT = \frac{\sum_{i=1}^{N} T_i \widehat{TE_i}}{\sum_{i=1}^{N} T_i}\right)$, and Average Treatment Effects on the Untreated $\left(ATUT = \frac{\sum_{i=1}^{N}(1-T_i)\widehat{TE_i}}{\sum_{i=1}^{N}(1-T_i)}\right)$. Detail discussions of the Bayesian ETPM and the estimation algorithms are given in Appendix A.

Identification strategy

For the purpose of identification, we use involuntary relocation as a weakly exogenous instrumental variable to be excluded from the outcome equations. The variable captures the degree of household's tie with community and hence the likelihood of participating community-based program. We established that households who were recently relocated from another village are less likely to sign up for the CBHI program. The instrument also meets the basic requirement that it must be exogenous in the outcome variables. In our estimation, identification is achieved through joint modeling with the exclusion restriction of the instrumental variable. In addition to dummy involuntary relocation of households, we also excluded membership in local microfinances from the outcome equation. The involuntarily relocation variable is a dummy variable indicating whether the household is resettled due to resettlement policy, evacuation due to disaster, jobs, or forced out by owner/parents. The idea is that tenured households with a long-standing tie to the community are more likely to participate in community-level programs, such as the CBHI schemes than those with a weaker tie.

The criteria for a good instrument are that it must significantly affect enrollment decisions but not the outcome variables significantly. If involuntary relocation affects households' catastrophic and impoverishing healthcare spending, it should only be through membership in the CBHI schemes. We tested whether the variable indeed significantly influence the decision to enroll in CBHI schemes but not the outcome variables. The test results show that households who involuntarily relocated from another community are less likely to participate in the CBHI schemes. Although there is no formal test to determine exogeneity, we conduct the overidentification test by jointly excluding involuntary relocation and microfinance membership from the outcome equations. In all models, the test results show that the models are overidentified suggesting that the two variables can be jointly excluded from the outcome equations.

4. Results and Discussions

4.1. CBHI Enrollment and Self-Selection

Table (3) presents the posterior means and standard deviations from the bivariate probit model of CBHI participation and the incidence of catastrophic spending. The results show that household demographic characteristics, educational level, health conditions and behavior, incomes, and wealth are significant determinants of CBHI enrollment. While age, marital status, and education of household heads increase the likelihood of enrolling in CBHI schemes, male-headed households are less likely to enroll. Similarly, health conditions and health behavior play important role in households' uptake of CBHI in that higher number of illness incidences and unhealthy behavior such as alcohol and tobacco consumption reduce the likelihood of enrollment. The results also show that higher level of education, income and wealth significantly increase the probability of enrollment implying that the poor and the less educated find the insurance package not affordable or less appealing to subscribe to.

Some of the observed variables which significantly determine enrollment also affect the outcome variables, highlighting the importance of self-selection on observed factors. For instance, households headed by older and married individuals are more likely to incur catastrophic spending, and at the same time, are more likely to enroll in CBHI schemes. This holds true for different thresholds of catastrophic spending. Similarly, other observed characteristics significantly affect enrollment decisions and the probability of catastrophic spending justifying our joint modeling of the participation and the outcomes equations.

However, self-selection arises not only on observables but also unobserved factors, such as preference toward risk and insurance. The correlation captures selection on the unobserved dimensions, is positive and statistically significant implying. It implies that enrollment decision is endogenous in that households who are more likely to enroll are also more likely to incur catastrophic spending.

The same is true in the headcount poverty model based on $1.00 per day poverty line (Table (4)) in which the estimated correlation term is positive and statistically significant implying that households with a higher likelihood of falling below extreme poverty due to out-of-pocket healthcare payments are more likely to sign up for the CBHI coverage. On the contrary, the correlation becomes negative and significant when we use moderate poverty line. It implies that households who are likely to fall below \$2.00 poverty line due out-of-pocket spending on healthcare have a lower chance of enrolling in the CBHI. With regards to endogeneity in the poverty gap model (based on \$1.00 per day poverty line), the correlation term for both the "hurdle" and the continuous parts are positive (see Table (5)).

Table (3): **Incidence of Catastrophic Spending**: Bivariate probit posterior coefficient estimates

	CBHI Enrollment		Threshold: 20%		Threshold: 30%		Threshold: 40%	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Intercept	-1.65*	(0.14)	-1.59*	(0.15)	-1.59*	(0.14)	-1.94*	(0.17)
CBHI			-1.76*	(0.06)	-1.75*	(0.08)	-1.79*	(0.07)
Head: Age	0.01*	(0.001)	0.01*	(0.001)	0.01*	(0.001)	0.01*	(0.001)
Head: Male	-0.31*	(0.05)	-0.14*	(0.05)	-0.14*	(0.05)	-0.17*	(0.05)
Head: Married	0.57*	(0.04)	0.38*	(0.04)	0.38*	(0.05)	0.35*	(0.05)
HH: Size	-0.01	(0.01)	-0.05*	(0.01)	-0.05*	(0.01)	-0.07*	(0.01)
Head educ: Primary	0.29*	(0.04)	0.04	(0.04)	0.04	(0.04)	0.02	(0.04)
Head educ: Sec/Voc/Univ	0.48*	(0.08)	0.03	(0.09)	0.03	(0.09)	0.001	(0.10)
HH: #of individuals w/ illness	-0.07*	(0.02)	0.33*	(0.01)	0.33*	(0.01)	0.31*	(0.02)
Alcohol use	-0.02	(0.04)	-0.10*	(0.04)	-0.10*	(0.04)	-0.14*	(0.04)
Cigarette use	-0.13*	(0.05)	-0.21*	(0.05)	-0.21*	(0.05)	-0.20*	(0.05)
# of wage earners	-0.01	(0.01)	-0.06*	(0.02)	-0.06*	(0.02)	-0.07*	(0.02)
2nd Cons. Quartile	0.12*	(0.05)	0.07	(0.05)	0.07	(0.05)	0.08	(0.05)
3rd Cons. Quartile	0.18*	(0.05)	0.11*	(0.05)	0.11	(0.06)	0.10	(0.06)
4th Cons Quartile	0.32*	(0.06)	0.17*	(0.06)	0.17*	(0.06)	0.29*	(0.07)
2nd Wealth Quartile	0.14*	(0.05)	-0.01	(0.05)	-0.01	(0.05)	-0.01	(0.05)
3rd Wealth Quartile	0.25*	(0.05)	-0.10*	(0.05)	-0.10*	(0.05)	-0.03	(0.06)
4th Wealth Quartile	0.33*	(0.06)	-0.10*	(0.05)	-0.10*	(0.05)	-0.05	(0.06)
Urban	-0.06	(0.07)	-0.03	(0.06)	-0.03	(0.06)	-0.13	(0.08)
Microfinance	0.32*	(0.03)						
Involuntarily Relocated	0.02	(0.05)						
Year 2005			-0.30*	(0.04)	-0.30	(0.04)	-0.36	(0.05)
Year 2010	1.49*	(0.04)	0.11*	(0.06)	0.11	(0.06)	0.09	(0.06)
District Dummies	Yes		Yes		Yes		Yes	
Covariance			0.87	(0.03)	0.87	(0.03)	0.87	(0.03)
Bayes Factor			0.00		0.00		0.00	
No. of obs.	26,193		26,193		26,193		26,193	

Note: We do not report coefficients of enrollment equations in different models of COOP as they are close to each other in magnitude and level of significance.

Table (4): **Headcount Poverty**: Bivariate probit posterior coefficient estimates

	CBHI Enrollment		USD 1.00/day		USD 2.00/day	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Intercept	-1.53*	(0.09)	-2.86*	(0.21)	-2.59*	(0.24)
CBHI			-1.49*	(0.17)	1.77*	(0.13)
Head: Age	0.006*	(0.001)	0.00	(0.00)	0.00	(0.00)
Head: Male	-0.30*	(0.04)	0.02	(0.07)	-0.10	(0.09)
Head: Married	0.56*	(0.03)	0.17*	(0.07)	-0.13	(0.10)
HH: Size	0.00	(0.01)	-0.01	(0.01)	-0.05*	(0.02)
Head educ: Primary	0.30*	(0.03)	0.13*	(0.06)	0.09	(0.08)
Head educ: Sec/Voc/Univ	0.53*	(0.06)	0.23*	(0.11)	0.03	(0.14)
HH: #of individuals w/ illness	-0.07*	(0.01)	0.18*	(0.02)	0.18*	(0.03)
Alcohol use	0.01	(0.03)	-0.08	(0.05)	0.20*	(0.06)
Cigarette use	-0.13*	(0.03)	-0.13	(0.07)	-0.14	(0.09)
# of wage earners	-0.01	(0.01)	-0.04*	(0.02)	-0.02	(0.03)
2nd Wealth Quartile	0.16*	(0.04)	0.14*	(0.07)	-0.27*	(0.11)
3rd Wealth Quartile	0.30*	(0.04)	0.20*	(0.07)	-0.15	(0.09)
4th Wealth Quartile	0.39*	(0.04)	0.19*	(0.08)	-0.15	(0.09)
Urban	-0.08	(0.05)	0.04	(0.09)	0.06	(0.13)
Microfinance	0.35*	(0.04)				
Involuntarily Relocated	0.08*	(0.04)				
Year 2005			-0.13	(0.07)	-0.15	(0.10)
Year 2010	1.50*	(0.03)	0.68*	(0.11)	-1.01*	(0.12)
District Dummies	Yes		Yes		Yes	
Covariance			0.77*	(0.07)	-0.84*	(0.05)
Bayes Factor			0.00		0.00	
No. of obs.	26,193		26,193		26,193	

Finally, our formal test of the null hypothesis of exogeneity in enrollment shows that the Savage-Dickey ratios are all zero, implying significant endogeneity in enrollment even after controlling for observed factors. Hence, ignoring endogeneity or assuming that CBHI is exogenous could lead to biased estimates of treatment effects.

Table (5): **Poverty Gap (USD 1.00/day poverty line):** ETPM posterior coefficient estimates

	CBHI Enrollment		Hurdle		Poverty Gap	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Intercept	-1.535*	(0.072)	-1.873*	(0.081)	7.1903*	(0.170)
CBHI			-0.172	(0.163)	-0.5815*	(0.270)
Head: Age	0.0059*	(0.001)	-0.004*	(0.001)	0.0008	(0.001)
Head: Male	-0.3051*	(0.027)	-0.118*	(0.029)	0.0081	(0.049)
Head: Married	0.5652*	(0.024)	0.244*	(0.036)	0.0138	(0.059)
HH: Size	-0.0013*	(0.005)	0.141*	(0.005)	-0.0826*	(0.008)
HH: #of individuals w/ illness	-0.0639*	(0.009)	0.120*	(0.008)	0.3025*	(0.014)
Alcohol Use	0.0126*	(0.021)	-0.280*	(0.019)	0.0101	(0.033)
Cigarette Use	-0.1292*	(0.025)	-0.028	(0.024)	-0.0476	(0.040)
Head educ: Primary	0.3031*	(0.021)	-0.010	(0.025)	0.1178*	(0.041)
Head educ: Sec/Voc/Univ	0.5279*	(0.042)	-0.355*	(0.047)	0.1955*	(0.088)
# of wage earners	-0.0081	(0.008)	0.040*	(0.007)	-0.0295*	(0.012)
2nd Wealth Quartile	0.1569*	(0.026)	-0.001	(0.025)	0.1366*	(0.041)
3rd Wealth Quartile	0.2974*	(0.027)	-0.195*	(0.029)	0.2115*	(0.050)
4th Wealth Quartile	0.3905*	(0.030)	-0.616*	(0.032)	0.322*	(0.062)
Urban	-0.0823*	(0.036)	0.127*	(0.033)	0.1814*	(0.054)
Microfinance	0.3967*	(0.024)				
Involuntarily Relocated	0.0739*	(0.033)				
Year 2005 Dummy			0.243*	(0.030)	-0.5244*	(0.055)
Year 2010 Dummy	1.4996*	(0.022)	0.438*	(0.090)	-0.0469	(0.139)
District Dummies	Yes		Yes		Yes	
Covariance			0.242*	(0.096)	0.317	(0.158)
Variance					1.990*	(0.083)
Bayes Factor			0.00		0.00	
Predicted Poverty Gap (2000 Prices)						
Whole Sample	1,454	(35)				
CBHI Enrolled	1,074	(71)				
Uninsured	2,200	(311)				
No. of obs.	14,880		14,880		14,880	

4.2. Treatment Effects

Table (6) presents the estimated ATEs on catastrophic spending from bivariate probit and simple probit models. The first two columns show the results for the whole sample, whereas the third and the fourth columns are for a subsample of poor households living under $1.00 per day. Although the treatment effects from simple probit model which assume exogneity in enrollment are negative and statistically significant, the magnitude is close to zero. This underscores that CBHI reduces the incidence of catastrophic spending by about 2 percentage points. However, due to endogeneity in CBHI enrollment, these estimates are substantially biased. Given the correlation term is positive and relatively large, the bias is expected to attenuate treatment effects towards zero.

Table (6): Average Treatment Effects on the Incidence of Catastrophic Spending: Bayesian Estimation of Bivariate and Simple Probit Models

	Whole Sample		The Poor Only (Below $1.00/day)	
	(1) Simple Probit	(2) Bivariate Probit	(3) Simple Probit	(4) Bivariate Probit
Threshold: 20%	-0.020*	-0.227*	-0.014	-0.281*
	(0.006)	(0.008)	(0.008)	(0.010)
Threshold: 30%	-0.022*	-0.227*	-0.022*	-0.219*
	(0.005)	(0.009)	(0.006)	(0.009)
Threshold: 40%	-0.017*	-0.182*	-0.019*	-0.168*
	(0.004)	(0.008)	(0.006)	(0.011)
No. of obs.	26,193	26,193	14,880	14,880

Our joint estimation of enrollment and the incidence of catastrophic spending controls for endogeneity by letting the error terms to be correlated. The estimates from this model (column (2)) show that after controlling for selection bias on observed and unobserved dimensions, the CBHI reduces the incidence of catastrophic healthcare spending (i.e. more 20% to 30% of non-food consumption expenditure in this case) by about 23 percentage points. Similarly, the CBHI reduces the incidence of spending more than 40% of non-food consumption expenditure on healthcare by 18 percentage points. Such a significant reduction in the incidence of catastrophic spending also holds for the extreme poor. For instance, among households living under $1.00 per day, the CBHI reduces the probability of spending more than 30% of non-food expenditure on healthcare by about 22 percentage points (see column (4)). These findings imply that regardless of the thresholds and poverty status, the program significantly reduces the incidence of catastrophic healthcare spending.

Table (7) shows the estimated ATEs on headcount poverty and poverty gap. The ATEs on the headcount poverty obtained from the simple probit model are very close to zero and not statistically significant. As stated above these estimates are, however, biased due to endogeneity. This is shown in the results from the bivariate probit model (column (2)) in which the CBHI coverage reduces the incidence of extreme poverty due to healthcare payments by about 8 percentage points. However, since the proportion of households who fall below the $1.00 poverty line due to healthcare payments is small to begin with (only 1.7% and 1.3% of the uninsured and the insured households, respectively), the impact in reducing poverty seems small but statistically significant. At a higher poverty line of $2.00 per day, the CBHI increases the incidence of moderate poverty by about 7 percentage points, implying that there is some non-linearity in the effects.

Table (7): Average Treatment Effects on Headcount poverty and Poverty Gap

	Simple Probit	Bivariate Probit	TPM	ETPM
Headcount ($1.00/day)	-0.008	-0.080*		
	(0.005)	(0.013)		
Headcount ($2.00/day)	0.004*	0.071*		
	(0.002)	(0.009)		
Poverty Gap ($1.00/day)			231	-1,127*
			(62)	(370)
Poverty Gap ($2.00/day)			519	-2,910*
			(104)	(1,427)
No. of obs.	26,193	26,193	14,880	14,880

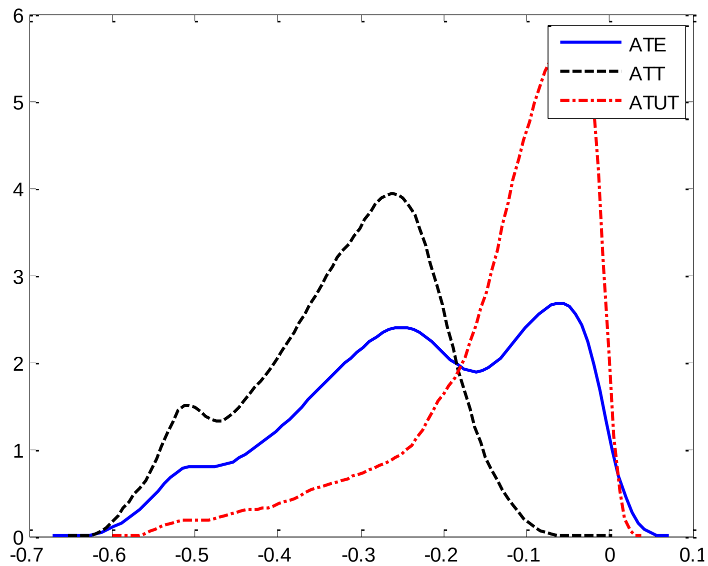
With regards to the impact on the poverty gap, we find that the program significantly reduces poverty gap. For instance, enrollment reduces the depth of extreme and moderate poverty by about 1,127 RwF and 2,900 RwF, respectively. The holds true for moderate poverty gap as well. Although the program seems to push some households below the moderate poverty line of $2.00 per day, it reduces the depth of poverty that results from out-of-pocket healthcare payments. Given that poverty gap is an improvement over the simple measure of poverty incidence measuring the amount of consumption or income shortfalls relative to the poverty line, we can infer that the net effect of the CBHI coverage is to reduce poverty which is caused by out-of-pocket healthcare payments.

Poverty gap could be considered as the cost of eliminating poverty relative to the poverty line. The results above therefore show that the CBHI program reduces the total cost of eliminating extreme poverty which is caused by out-of-pocket healthcare spending by about $2.89 and moderate poverty by about $7.44, in 2000 prices.

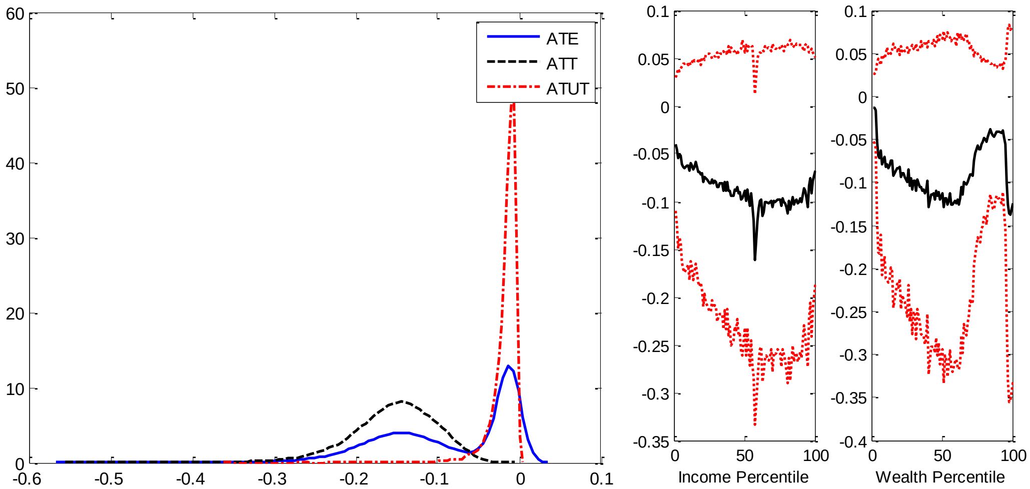
Averages conceal as much as they reveal when it comes to the distribution of impacts. As households respond differently to an otherwise identical treatment due to various factors, it is imperative to assess the distribution of treatment effects. In Figures (4) – (6) we show the distributions of treatment effects and plots by income and wealth deciles. As the figures clearly show, the distribution of the treatment effects on the incidence of catastrophic spending, the headcount poverty, and the poverty gap is not degenerate and hence confirm the presence of heterogeneity in treatment effects. Similarly, the distribution of treatment effects on the treated (black dotted lines) and the untreated (red dotted lines) groups are different further revealing the heterogeneous impacts.

Figure (4): Distributions of Treatment Effects

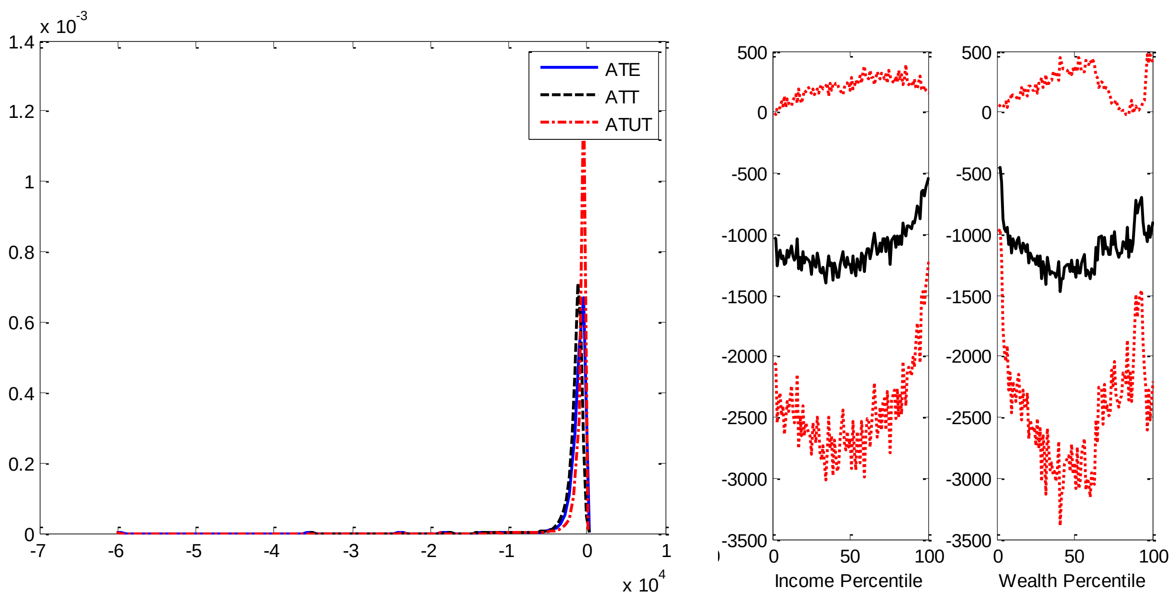
a) the Incidence of Catastrophic Spending (30% Threshold)



b) Headcount Poverty ($1.00 per day)



c) Poverty Gap ($1.00 per day)



4.3. Sensitivity Analysis and Robustness Check

For the purpose of hypothesis testing using the Savage-Dickey ratio, we impose informative prior on the covariance terms. Imposing such informative prior could pull the estimated coefficients towards zero and potentially propagates to other model parameters and the estimated treatment effects. Hence, we check for the sensitivity of our estimated treatment effects to our prior selections by imposing a less informative prior of $TN(0,2I)$ and a more informative prior of $TN\left(0,\frac{1}{8}I\right)$. The results in Table (8) show that the estimated ATEs, the covariance terms and other model parameters remain stable for different prior selections and hence confirm that the results are not sensitive to our choice of priors.

Table (8): Sensitivity Analysis: Sensitivity to informative prior selections

	COOP (Threshold: 30%) Bivariate Probit		Headcount Poverty ($1.00.day) Bivariate Probit		Poverty Gap ($1.00/day) ETPM			
					Hurdle		Expected Poverty Gap	
	c = 1/8	c = 2	c = 1/8	c = 2	c = 1/8	c = 2	c = 1/8	c = 2
ATE	-0.225*	-0.229*	0.074	0.075	-0.294*	-0.295*	-406*	-398*
	(0.011)	(0.007)	(0.010)	(0.011)	(0.005)	(0.005)	(66)	(69)
Covariance	0.859*	0.876*	-0.798*	-0.809*	0.889*	0.888*	-0.403*	-0.407*
	(0.041)	(0.022)	(0.059)	(0.066)	(0.008)	(0.008)	(0.028)	(0.028)
Variance					1.951*	1.948*	1.951*	1.948*
					(0.031)	(0.030)	(0.031)	(0.030)
Bayes Factor	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Finally, we also estimate the effects of CBHI using frequentist methods, specifically the Linear Probability Model (LPM) using OLS and IV methods. In principle, the coefficients from these methods are not comparable with coefficients from the Bayesian methods. However, for robustness check and getting some sense on the direction and the magnitude of the biases arising from endogeneity, we estimate the ATEs on various outcomes using OLS and IV methods (see Tables (B.1) – (B.3) in Appendix B). Not surprisingly, the estimated treatment effects from OLS are biased towards zero, and the magnitude of estimates from the IV method is much higher.

The IV estimates show that the ATEs on the incidence of spending more than 20%, 30%, and 40% of non-food expenditure on healthcare is -22, -20, and -22 percentage points, respectively. While the ATEs from the IV method is very close to the estimates obtained from the Bayesian bivariate probit model and the ATEs from simple OLS estimates are closer to the results from the simple Bayesian probit model. Similarly, the effects on the poverty gap shows the same pattern but with a larger magnitude in the IV estimates. This could be due to the fact that the IV estimates do not adjust for the high proportion of zero and possibly due to heteroscedasticity in the poverty gap. Generally, we can deduce that our estimates using various models affirm that the CBHI program significantly reduces the incidence of catastrophic spending, decreases the incidence of extreme poverty and the poverty gap, but slightly increases the incidence of moderate poverty.

5. Concluding Remarks

Households in developing countries are vulnerable to catastrophic financial risks and impoverishment due to large medical bills. Often, they do not have access to formal healthcare financing systems such as health insurance or tax-based public healthcare financing systems. Rwanda is one of the few African countries to implement the CBHI schemes as an integral part of its national healthcare financing system. However, the impact of the program in reducing financial catastrophe and impoverishment due to out-of-pocket healthcare payments is not well documented. This study contributes to the literature by investigating the causal effects of this grass-roots level health insurance schemes on health-related financial risks and poverty.

Using a nationally representative observational dataset from Rwanda, we estimate the impacts of the CBHI program on the incidence of catastrophic healthcare spending, the incidence of poverty, and the poverty gap. We estimate the models using Bayesian technique, addressing biases arising from endogeneity in health insurance choice, censoring in healthcare payments, and heterogeneity in treatment effects. Our estimates show that the program significantly reduces catastrophic healthcare spending. We also find that the program significantly reduces the incidence and depth of poverty due to out-of-pocket payment for healthcare services. The findings from this study show that in addition to increasing utilization of modern healthcare services, well-designed CBHI systems significantly reduce health-related financial risks and impoverishment.

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Appendix A: Bayesian Extended Two-Part Model and Estimation Algorithm

The model in equation (1) can be written in a three-equation system as follows:

$$T_i^* = \beta^T w_i \qquad + \varepsilon_i^T, \qquad (A.1)$$

$$h_i^* = \beta^h x_i + \gamma^h T_i + \varepsilon_i^h, \qquad (A.2)$$

$$g_i^{\Delta *} = \beta^g x_i + \gamma^g T_i + \varepsilon_i^g, \qquad (A.3)$$

where $T_i = 1(T_i^* > 0)$, $h_i = 1(h_i^* > 0)$, $g_i^{\Delta} = 1(h_i^* > 0)\exp\left(g_i^{\Delta *}\right)$, $1(\cdot)$ is indicator operator, $\left\{T_i^*, h_i^*, g_i^{\Delta *}\right\}$ are the latent variables, $\{\gamma^h, \gamma^g\}$ are treatment effects parameters, $\{\beta^T, \beta^h, \beta^g\}$ are vectors of slope parameters to be estimated, $\{\varepsilon_i^T, \varepsilon_i^h, \varepsilon_i^g\}$ are the error terms, $w_i = [x_i\ z_i]$ is again a vector of covariates in the selection equation, and z_i is a vector of exogenous variables excluded from x_i. In the ETPM, we assume that ε_i^h and ε_i^g are independent conditional on ε_i^T which renders a simpler model given by

$$h_i^* = \beta^h x_i + \gamma^h T_i + \sigma_{Th}\varepsilon_i^T + v_i^h \qquad (A.4)$$

$$g_i^{\Delta *} = \beta^g x_i + \gamma^g T_i + \sigma_{Ty}\varepsilon_i^T + v_i^g. \qquad (A.5)$$

where σ_{Th} and σ_{Tg} are the covariances capturing selection on unobservables, $v_i^h \sim n(0,1)$ and $v_i^g \sim n\left(0, \sigma_g^2\right)$ are independent, and $corr\left(\varepsilon_i^T,\ v_i^h\right) = 0$ and $corr\left(\varepsilon_i^T,\ v_i^g\right) = 0$.

In a Bayesian estimation framework, Model (i) and Model (ii) can be estimated using data augmentation and MCMC simulation techniques (Tanner and Wong, 1987; Albert and Chib, 1991). Then, the joint conditional posterior distribution of the parameters and the latent variables of the binary-treatment and the binary-outcome models can be written as

$$p(\Theta, T_i^*, d_i^* | T_i, d_i, w_i, X_i) \propto [p(T_i, d_i, T_i^*, d_i^* | w_i, X_i, \Theta)]p(\Theta)p(\Theta_0), \qquad (A.6)$$

where $X_i = [x_i\ T_i\ \varepsilon_i^T]$, $\Theta = \{\beta^T, \beta^d, \gamma^d, \sigma_{Td}\}$ is the set of parameters to be estimated, and $p(\Theta_0)$ is the prior distribution. Similarly, the joint conditional posterior distribution for the ETPM is given by

$$p\left(\Theta, T_i^*, h_i^*, g_i^{\Delta *} | T_i, h_i, g_i^{\Delta}, w_i, X_i\right) \propto \left[p\left(T_i, h_i, g_i^{\Delta}, T_i^*, h_i^*, g_i^{\Delta *} | w_i, X_i, \Theta\right)\right]p(\Theta)p(\Theta_0), \quad (A.7)$$

where $\Theta = \left\{\beta^T, \beta^h, \beta^g, \gamma^h, \gamma^g, \sigma_{Th}, \sigma_{Tg}, \sigma_g^2\right\}$ is a vector of parameters to be estimated.

In both models, we specify the priors for the slope parameters and the variance to be non-informative. Particularly, we specify non-informative conjugate normal distributions for the slope parameters with mean zero and variance 10 (i.e., $N(\mu_0 = 0, V_0 = 10I_K)$), and an inverse gamma distribution for the variance $\sigma_{g0}^2 \sim ig\left(\frac{\nu}{2}, \left(\frac{c}{2}\right)^{-1}\right)$, where $\nu = 10$ and $c = 5$.

Once the parameters are estimate, the estimated treatment effect $\widehat{TE}_\iota(x_i)$ is calculated through Monte Carlo integration over the post-convergence parameters obtained from the MCMC iterations as

$$\widehat{TE}_\iota(x) = E_\theta[iTE(X;\theta)] \approx \frac{1}{R}\sum_{r=1}^{R} iTE\big(X;\tilde{\theta}_R\big), \qquad (A.8)$$

where $\tilde{\theta}_R$ is a vector of post-convergence parameters. The calculated $\widehat{TE}_\iota(x)$ gives us the whole distribution of treatment effects from which one can obtain the usual summary statistics such as Average Treatment Effects$\left(ATE = \frac{1}{N}\sum_{i=1}^{N} \widehat{TE}_\iota\right)$, Average Treatment Effects on the Treated $\left(ATT = \frac{\sum_{i=1}^{N} T_i \widehat{TE}_\iota}{\sum_{i=1}^{N} T_i}\right)$, and Average Treatment Effects on the Untreated $\left(ATUT = \frac{\sum_{i=1}^{N}(1-T_i)\widehat{TE}_\iota}{\sum_{i=1}^{N}(1-T_i)}\right)$. The estimation algorithms are given in Appendix A.

Estimation Algorithm

In this section, we present the MCMC algorithm to estimate a bivariate probit model for binary treatment and binary outcome model and ETPM for binary treatment and censored continuous outcome. The estimation code for both modes is written in Matlab and tested on artificially generated data before applying to the real data. Box (1) and (2) presents the MCMC steps. While the details of the bivariate probit model can be found in Koop et al. (2007) and other textbooks, the algorithm for ETPM can be found in studies such as Deb et al. (2006), Li and Trivedi, (2014), and Woldemichael et al. (2015). We run the MCMC iterations 10,000 times dropping the first 5,000 draws as burn-ins. Moreover, we assess the convergence of the MCMC draws using trace plots and formal convergence diagnostic test developed by Geweke (1992).

Box 1: MCMC steps for Bivariate Probit model (Binary Treatment Binary Outcome Model)	
Step 1:	draw the latent variable T_i^* from its conditional truncated normal distribution
Step 2:	draw the latent variable d_i^* from its conditional truncated normal distribution
Step 3:	draw β^T for its conditional normal distribution
Step 4:	draw $\theta^d = [\beta^d, \gamma^T]$ from the joint conditional normal distribution
Step 5:	Draw σ_{Td} from the conditional truncated normal distribution

Box 2: MCMC steps for ETPM (Binary Treatment – Censored Continuous Outcome Model)	
Step 1:	draw the latent variable T_i^* from its conditional truncated normal distribution
Step 2:	draw the latent variable h_i^* from its conditional truncated normal distribution
Step 3:	for $i = 1, \dots, n < N$ such that $h_i = 0$, draw the latent variable y_i^* from its conditional normal distribution, otherwise set $g_i^{\Delta *} = \ln(g_i^{\Delta})$.
Step 4:	draw β^T for its conditional normal distribution
Step 5:	draw $\theta^h = [\beta^h, \gamma^h]$ from the joint conditional normal distribution
Step 6:	Draw σ_{Th} from the conditional truncated normal distribution
Step 7:	draw $\theta^g = [\beta^y, \gamma^g]$ from the joint conditional normal distribution
Step 8:	Draw σ_{Tg} from the conditional normal distribution
Step 9:	draw σ_g^{-2} from the conditional gamma distribution

Hypothesis Testing

We formally conduct hypothesis testing on whether CBHI enrollment is endogenous, i.e., $H_0: \sigma_{Td} = 0$ for the bivariate probit model and $H_0: \sigma_{Th} = \sigma_{Tg} = 0$ for the ETPM, using Bayes Factor. There are various methods to conduct hypothesis testing and model comparison in the Bayesian estimation framework. In this paper, we use the Savage-Dickey method which is simple and commonly used in the literature such as Deb et al (2006) and Li and Trivedi (2014). To conduct the test using Savage-Dickey ratio, one needs to place informative priors on the covariance terms. For this purpose, we follow the literature and specify a truncated normal distribution with mean zero and variance $\frac{1}{2}$, i.e., $TN_{[-1,1]}\left(0, \frac{1}{2} I\right)$. The Savage-Dickey Bayes factor for the ETPM is given by

$$B_{0,1} = \frac{p\left(\sigma_{Th} = \sigma_{Tg} = 0 | X, \theta\right)}{p\left(\sigma_{Th} = \sigma_{Tg} = 0\right)}, \qquad (A.9)$$

where the numerator is the joint posterior density of σ_{Th} and σ_{Ty} evaluated at zero, whereas the denominator is the prior density evaluated at zero. Specifically, $p(\sigma_{Th} = 0, \sigma_{Tg} = 0)$ is calculated form a multivariate normal pdf with mean $\mathbf{0}_{2\times1}$ and covariance matrix $\frac{1}{2} I_{2\times2}$ evaluated at zero. The Bayes Factor for the bivariate model is calculated in a similar fashion from normal pdf with mean zero and variance 0.5. The data favors the null hypothesis if the Savage-Dickey Bayes factor is greater than 1, otherwise the alternative.

Appendix B: Additional Tables and Figures

Table (B.1): Linear Probability Model: OLS and IV estimates of the effect of CBHI on Catastrophic Spending (Classical OLS and IV Estimates)

	OLS (LPM)			IV (LPM)		
	Thresholds					
	20%	30%	40%	20%	30%	40%
I. The whole sample						
CBHI	-0.023*	-0.023*	-0.016*	-0.217*	-0.198*	-0.224*
se	(0.005)	(0.005)	(0.004)	(0.086)	(0.071)	(0.062)
p-value	0.000	0.000	0.000	0.012	0.005	0.000
Sargan Statistics				0.017	0.135	0.194
p-value				0.898	0.713	0.659
No. of obs.	26,193	26,193	26,193	26,193	26,193	26,193
II. The Poor below USD 1.00/day						
CBHI	-0.015	-0.020*	-0.015*	-0.150	-0.249*	-0.312*
se	(0.008)	(0.006)	(0.005)	(0.12)	(0.10)	(0.09)
p-value	0.051	0.002	0.004	0.204	0.013	0.001
Sargan Statistics				0.372	1.667	2.211
p-value				0.542	0.197	0.137
No. of obs.	14,880	14,880	14,880	14,880	14,880	14,880

Table (B.2): Linear Probability Model: OLS and IV estimates of the effect of CBHI on Headcount Poverty

	OLS (LPM)		IV (LPM)	
	$1.00/day	$2.00/day	$1.00/day	$2.00/day
CBHI	-0.001	0.003*	0.036	0.051*
se	(0.002)	(0.001)	(0.031)	(0.023)
p-value	0.777	0.067	0.2409	0.0246
Sargan Statistics			0.348	0.215
p-value			0.555	0.643
No. of obs.	26,193	26,193	26,193	26,193

Table (B.3): OLS and IV estimates of the effect of CBHI on Poverty Gap (Whole Sample)

	OLS		IV	
	$1.00/day	$2.00/day	$1.00/day	$2.00/day
	I. The Whole Sample			
CBHI	-84	-136	-3,016*	-77
se	(62)	(139)	(997)	(2135)
p-value	0.178	0.327	0.0025	0.9712
Sargan Statistics			1.143	0.182
p-value			0.285	0.669
No. of obs.	14,880	22,221	14,880	22,221

Figure (B.1): Histogram of the difference between Pre – and Post – Healthcare Payment Poverty Gap

($1.00 per day poverty line)