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Community based health insurance schemes (Mutuelles) in Rwanda: *an evaluative note using household surveys*

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Community based health insurance schemes (*Mutuelles)* in Rwanda: *an evaluative note using household surveys*[1]

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Abstract

Community-based health insurance schemes (*Mutuelles*) in Rwanda are one of the largest experiments in community based risk-sharing mechanisms in Sub-Saharan Africa for health related problems. This study examines the impact of the program on demand for modern health care, mitigation of out-of-pocket catastrophic health expenditure and social inclusiveness based on a nationally representative household survey using traditional regression approach and matching estimator popular in the evaluation literature. Our findings suggest that *Mutuelles* have been successful in increasing utilization of modern health care services and reducing catastrophic health related expenditure. According to our preferred method, much higher utilization of health care services was found among the insured non-poor than insured poor households, with comparable effect on income protection. This reinforces the inequity already inherent in the *Mutuelles* system.

Key Words: demand for health services, catastrophic health expenditure, average treatment effects, endogenous dummy variable, matching estimator

1. Introduction

According to WHO (2005) 100 million people every year are driven into poverty due to catastrophic health expenditure. It is imaginable that most reside in resource poor settings such as Sub Saharan Africa (SSA) with very weak modern health care systems and in most cases without any functioning health insurance schemes (e.g WHO, 2003; Carrin et al, 2005) . The result is high disease burden that has a risk of propagating a sickly, unproductive labor force. In Sub-Saharan Africa, formal and well functioning health insurance schemes generally exist for the very few who are employed in the formal sector. For the majority, health care is accessed through out-of-pocket expenditure, which in many instances may not lead to optimal use of health care services. As a result, expenditure on heath related needs in some countries could be substantially high (see Figure 1 & Figure 2) with visible divergence across the income divide. Households in poorer countries generally tend to spend as much as those living in relatively richer countries, but evidently with worse health outcomes. One of the reasons could be lack of functioning health insurance scheme to protect households from illness related income or expenditure shocks. Formal health insurance schemes for the self-employed and rural farmers are difficult to institute for a number of reasons. Community Based Health Insurance Schemes (CBHISs) are promising alternatives for a cost sharing health care system which hopefully also leads to better utilization of health care services, reduce illness related income shocks and eventually lead to a sustainable and fully functioning universal health care system.

Traditional solidarity organizations exist in a rudimentary form to deal with health related shocks in some parts of Africa and have provided the basis for the movement towards CBHISs that emerged in response to failure by the state and market to provide such services. Ghana, Senegal and Rwanda are among the leading countries that experimented on the idea of CBHISs as a national health program in Africa (see Juting, 2003 for review)

CBHISs in Rwanda are interesting case study for a number of reasons. The first and most important is that the country has scaled up coverage of CBHISs from just around 35% in 2006 to almost 85% in 2008, an exponential growth in a space of two years in the middle of uncertainty on its potential impact on health service utilization and protection from unforeseen health related income or consumption shocks. Such rapid growth and coverage is unprecedented in the history of CBHISs (Mladovsky and Mossialos, 2007). Secondly, CBHIs in Rwanda have been accorded central place by policy makers so that they are integral parts of the country’s health program, with a strong administrative and political support for their expansion and functioning. Third, the experiment has attracted so much interest that other countries are considering the Rwandan model as an alternative vehicle for health sector financing and delivery of basic health services.

Some of the strong critiques of the program argue that CBHIs have the potential to further alienate the extreme poor from utilizing health services for at least two main reasons. First, the flat premium rate (about $2 USD per year per person) is already too high for the very poor so that given a choice they would rather defer health care expenditure until it is vitally needed. Secondly, even if extreme poor people become members of CBHIs, they may not fully utilize its provisions since all is not free. There are other layers of expenses to be born such as transport, prescription drugs, and others including the opportunity cost of time, especially for the casual laborers. Thus, in short the CBHIs could be inefficient and iniquitous for the health service that is heavily subsided by funds coming from the treasury as well as international aid. This study attempts to contribute to this debate by providing some evidence on the relationship between membership to CBHIs and key indicators that measure intended outcomes. So, the research questions addressed in this paper are: have the CBHIs in Rwanda assisted households to change their behavior towards modern health care utilization? Has it been successful in averting catastrophic health related expenditure? Most of all, how do the poor fare in both instances?

Ideally such issues could have been addressed with little or no bias if the data were generated from a fully randomized experiment. In our case we have access to data generated from a field survey such that there is no guarantee that membership to CBHIs is wholly random. There are potential selection biases generated from at least the following sources. Households with pre-existing condition may self-select into the insurance program raising the classic problem of moral hazard. Or, relatively richer households may find it cheaper to subscribe to the insurance scheme more than the poor, though their behavior towards health care utilization or income protection could not be attributed solely to the insurance scheme. This is plausible given the flat insurance premium rate that is inherently discriminatory against the poor. There are also other unobserved factors such as tenacity of local administrations to get compliance for accelerated subscription, etc. All of these factors could lead to biases on any estimator that attempts to establish causality running from membership to CBHISs to outcomes.

This paper uses both the traditional regression approach as well as the matching estimator popular in the evaluation literature to estimate the effect of membership to CBHISs on household demand for health care services and income protection bearing in mind the endoenity issue raised in the preceding paragraph. In the regression approach, since both dependent and independent variables are discrete, estimation routine is some how complicated (Heckman, 1974). Typically, one would require a good instrument that impacts health and income only through membership to CBHISs. As in most empirical works, this is a formidable challenge. We identified two instruments from the data that we used to undertake weak exogenity test as in Smith and Blundell (1986) where residuals from the first stage regressions including the instruments and other covariates would have no explanatory power on our outcome variables. Since weak exogenity could not be rejected, we resorted to simple probit models to obtain coefficients that impacted on outcome variables[2]. The matching estimator also has a potential to control for selection biases arising only from observed covariates. Our result is indicative of significant impact on health care utilization and household protection form negative health related consumption shocks based on two methods. The matching estimator identified the direction of impact between "treated" and "control" groups under a number of scenarios which in general favor the non-poor subscribers over the poor ones. The rest of the paper is organized as follows. Section 2 provides a sketch of the analytical framework, Section 3 describes the data and definition of variables, Section 4 discusses the results and Section 5 concludes the paper.

2. Estimation methods

2.1. Analytical framework

Do community-based health insurance increase schemes increase demand for modern health care system in a resource poor setting? Can they protect households from large unforeseen expenditure shocks with a potential to have permanent damage on livelihoods? Are the poor excluded from utilization of modern health care despite being insured? To capture the role of *Mutuelles* (CBHISs) in allowing better utilization of health care services, mitigation of catastrophic health related expenditure and social inclusion, we employ the traditional regression approach as well as the matching estimator popular in the evaluation literature.

The econometric model commonly used to establish causal relationship between membership in the CBHISc and some outcomes such as demand for health services, income protection and

[2] Bi-variate probit specification also returned statistically insignificant correlation between the structural equation and the reduced auxiliary equation.

others when at least one of the regressors, in this case, membership into CBI is suspected to be endogenous (Smith and Blundell, 1986) is given by the following relations.

$$y'_{1i} = 1[y'_{2i}\gamma_1 + x'_{1i}\beta_1 + u_{1i} > 0] \qquad (1.1)$$

$$y'_{2i} = 1[x'_i\pi_2 + v'_{2i} > 0] \qquad (1.2)$$

$$\begin{bmatrix} u_{1i} \\ v_{2i} \end{bmatrix} \sim NI\left(0, \begin{pmatrix} \sigma_1^{\ 2} & \sigma'_{12} \\ \sigma_{21} & \Sigma_{22} \end{pmatrix}\right)$$

Where $x'_i = (x'_{1i}, x'_{2i})$ is a vector of observations on K (=K1+ K2), and y_{1i} and y_{2i} are vectors of dependent variable and endogenous regressor (in our case dummy if a household is a member of CBHISs), respectively. The usual identification assumptions are made. Equations (1.1) and (1.2) belong to a class of systems equations where estimation of the underlying parameters can be done jointly using bivariate probit model under the normality assumption for the error terms. There are also other approaches suggested to estimate (1.1) and (1.2), starting from Heckman's (1974) two-step procedure to the recursive full maximum likelihood estimation as discussed in Madalla (1983). To utilize the above set up, two instruments have been identified from the data that are believed to be correlated with the regressor but uncorrelated with the error term of equation (1.1). One of the instrument is constructed from information provided by each household at cluster level so that the bias introduced by individual choice is some how diluted[3]. The second instrument is a dummy whether or not a household reported to have a title deed for land owned. This is potentially important indicator of district level administrative efficiency that could also impact participation in CBHISs and thus health service utilization. We used these instruments along with other covariates to test whether the error terms in equations (1.1) and (1.2) are not correlated. If the test is rejected, then, joint estimation of equation (1.1) and (1.2) have to be made or other instrumental variable estimation methods have to be applied.

The matching estimator popularized by Rosenbaum and Robin (1983) is frequently applied in program evaluation studies where the data is organized along "treated" vs "control" dichotomy conditional on observed covariates. Such a dichotomy allows estimation of three statistics

[3] $C_i = \dfrac{E_i - D_i}{N_i - 1}$ where Ei is enrollment at cluster level, Di is dummy if household is a member, and Ni is total number of households in the cluster.

relevant for evaluation. The Average Treatment Effect (ATE), compares outcomes between "treated" vs "control" group by taking randomly selected individuals from both samples so that impact of a program is evaluated directly. The Average Treatment Effect on the Treated (ATT) evaluates program impact among randomly selected individuals within the group exposed to the treatment. The Average Treatment Effect on the Control (ATC) measures the impact of a program among randomly selected individuals within the control group. We report all three estimates for the effect of CBHISs on our outcome variables.

Formal statement of the matching estimator may be outlined as follows. Evidently, impact of program evaluation proceeds with at least the following information: D_i, a dummy if the individual is treated or not , Y_i realized outcome due to exposure to the treatment and X_i represents a set of exogenous covariates used as control variables. The following definition holds:

$$Y_i = Y_i(D_i) = \left\{ \frac{Y_i^c if \quad D_i = 0}{Y_i^c \ if \ D_i = 1} \right\} \qquad (2)$$

Matching estimators defined (2) are identified under two very important assumptions (see for exposition Imbens, 2004): The assumption of uncofoundness or sometimes known as ignorable treatment assignment (Moreno-Serra, 2007) states that treatment assignment of a given individual is independent of potential health outcomes with and without treatment if observable covariates are held constant. Essentially this implies that theoretically the researcher has full information on the subjects under study so that there are no unobserved factors simultaneously correlated with the outcome of interest and the decision to participate in the treatment. The second most important assumption is that there is a positive probability of participation in the program at all values of the covariates X, known as the assumption of overlap. This implies that there are other factors than those in X that influence participation in the program so that the covariates are not linear predictors of participation in the program. Thus, barring omitted variable bias, matching estimators assume that any difference in health outcome between treated and untreated individuals is mainly due to the effect of the treatment.

Matching in the literature has been commonly implemented through a propensity matching score often based on probit or logit estimation of outcome variables and use the probability estimates as basis for matching. Recently Abadi and Imbens (2006) have shown that large sample properties of propensity matching scores have not been available until recently and proposed instead a simple matching method based on the notion of nearest neighbor matching or minimum distance across the covariates for each observation unit which does not assume any functional form (Abadie and Imbens, 2009).

The conceptual parallel between the traditional regression approach and matching estimators is discussed in Angirist (2001), where the most important factor is played by the context in which the identification assumption in the causality relationship is laid out. Theoretical relations provide insights into what constitutes endogenous and the necessary assumptions required to establish identification. In our case, membership to CBHISs is driven by household specific factors such as income, schooling, and occupation, age, etc (see Section 3 & 4 below) only to a limited extent. There are significant exogenous factors such as pressures by local administrators who operated against tight deadlines to increase membership into the CBHISs over a period of time. Thus, local conditions also play an important role, sometimes in a rather random way. Thus, if the unobserved factors , such as these ones, could influence membership in CBHISs but not realized health outcomes, still both regression models and matching estimators return valid result, with minimum bias. The regression approach lends itself to the close examination of endogenity by undertaking tests using potential instruments. The result indicates that residuals from regressions on a set of covariates and instruments have not been found to have any explanatory power suggesting that membership into CBHISs is weakly exogenous (Blundell and Smith, 1986). A fully specified simultaneous bivariate probit model also returned an insignificant contemporaneous correlation of error terms across equations. Along these lines, simple probit could be used to estimate the effect of membership in CBHISs on realized health related outcomes. The same applies to matching estimators with the option of not assuming any functional form that may even be preferred. In this regard, our assumption that observed covariates are weakly exogenous or unobserved effects does not affect both dependent and independent variable, though strong, seems valid in this context.

3. Data and variables definition

The data used in this study was collected in 2005/06 covering around 6,900 households with about 35,000 individual histories. The data is a typical living standard survey where information on household demographics, educational attainment, health, consumption, income sources, migration, agriculture, labor market condition, household assets, living conditions and other variables were collected. Using this data has the advantage of generalizability but could suffer from the presence of confounding factors on key variables of interest.

For this study, we have two dependent variables that we believe could be influenced by household decision to join the CBHSs. The first is utilization of modern health care. This variable is important in the Rwandan setting because in the absence of any insurance, households would have to rely on out-of-pocket expenditure to meet health related needs. This is the main drive behind the government's decision to use CBHISs as choice of instrument for the country's health program. The other obvious attendant benefit of having health insurance is whether or not the household is protected from large, unforeseen health related expenses. Thus, if the insurance scheme is fully functional and benefits are realized by members, then, one would expect improvements in utilization of health care facilities and also protection from illness related consumption shocks. We defined health facility utilization as a dummy whether or not a household sought treatment following illness episodes. Certainly this could be driven by many factors such as income, gravity of illness and other factors as availability of health centers in nearby areas. To capture income shocks, we defined a dummy variable where a household's current health expenditure is "catastrophic". There are no clear cut-off points in the literature on what level of health expenditure as a share of per capita is considered as catastrophic. Some use around 20%, others take larger values. In our case, given the low income level of the country, we have defined catastrophic expenditure as the top percentile in the distribution of health expenditure as a share of per capita consumption expenditure.

Table 1 suggests that for almost all possible socio-economic covariates, insured households tended to utilize public health services more than uninsured households. Similarly, Figure 3 and Figure 4 clearly depict profile of health related expenditure paraded from the poorest to the richest both for insured and uninsured households. The result is very suggestive of significant income shock protection. The drop-lines are more pronounced for uninsured than insured households. One could visualize an algebraic expression of Figures 3 and 4 as defining a weighted index of some sort of health related vulnerability, where *xi* stands for total consumption expenditure, *hi* is household expenditure on health related services and *i* is a ranking from poorest to richest households ($I_i = 1 - \frac{\sum i(x_i - h_i)/z}{\sum ix_i / z}$)[4].

For the model based estimations, we used the following control variables: Age of the head of the household, household size, sex of the head of the household, marital status, log consumption in adult equivalent, main sector of activity, level of schooling, dummies for 30 districts, dummies for illness and disability conditions, dummies for land right certifications, etc..

[4] We used a variation of this definition to construct a variable to capture income protection induced by insurance schemes.

4. Discussion of results

The results based on simple probit model are summarized in Table (4) where the marginal effects for alternative sub-groupings are reported. The findings suggest that membership into CBHISs had a potential of increasing health care utilization by about 15% following an illness episode. The effect is slightly higher for poor households than the non-poor. With regard to catastrophic expenditure, there is significant effect returned by the probit model where insured households had a much lower probability of experiencing catastrophic expenditure compared to the uninsured and more so among the poor than the non-poor. It is also important to be careful about the robustness of the simple probit model to several unobserved factors despite the weak exogenity assumption provided by the test. Perhaps under the circumstances the matching estimator could be able to isolate the effects of observed covariates much more effectively than the simple probit specification and it has also the added advantage that the estimator does not assume any functional form on the error terms (see for example, Barros and Machado, 2008).

The results from the matching estimator generally provide a much rosy picture of the effect of CBHISs on the variables of interest. Table (5) reports the average treatment effect over all samples of membership to CBHISs on health service utilization and income protection for all households and subset of poor and non-poor households. The results indicate that households that were members of the CBHISs had a 15 percentage point higher utilization of health care facilities than uninsured ones following an illness episode. In this regard, the degree of utilization is much higher among the non-poor than the poor, which also in the Rwandan setting makes a lot more sense since the non-poor literally pay much less for the insurance premium than the non-poor and also tended to have higher subscription rates to the program.

The matching estimator provides also an opportunity to compare the effect of membership to the CBHISs among the insured commonly referred to as the Average Treatment Effect of the Treated (ATT) and among the uninsured known as Average Treatment Effect of the Control group (ATC). The ATT provides what the impact of membership on the outcome variables has been without resort to the control group. It measures the extent to which insured households for instance utilized health care services in their own right. The result reported in Table 6 suggests that utilization of modern health care services among the insured did not have statistically significant effect on health utilization, particularly among the poor. The non-poor did show 21 percentage point increase in the use of health services. In other words, the arrival of the health insurance scheme certainly has increased health service utilization significantly among the non-poor. The CBHISs succeeded however in reducing significantly health related consumption shocks in all households, more among the poor than the non-poor. This result is very encouraging since health related shocks have the potential of persisting for a long time in typical poor households.

ATC measures the potential effect of the CBHISs by matching households only in the sample who were not insured. The estimator recovers the average effect of membership to CBHISs from a random sample of uninsured households. The result as reported in Table 7 suggests that if the insurance scheme was extended to non-members, heath utilization would increase by 18 percentage points. This figure is close to 30 percentage points for non-poor households and about 10 percentage points among poor households. With respect to income protection, the potential of CBHIs is still very high. It could reduce catastrophic expenditure by 17 percentage points and much more significantly among the poor than the non-poor households. Overall the matching estimator indicates stronger evidence of better utilization of health care facilities and income protection due to CBHISs in Rwanda.

5. Conclusions

Rwanda is one of the few countries in Africa that has taken CBHISs to a great length. Health insurance coverage increased dramatically in recent years where CBHISs service to 85% of the population amidst lingering concerns on whether they are effective and equitable instruments for the delivery of basic health care services. Rwanda's experience is also attracting attentions beyond its boarders where governments burdened by rising health care costs are looking towards such innovative schemes. This study is a first attempt to formally analyze whether or not CBHISs attained its intended objectives using traditional regression approach and matching estimator popular in the evaluation literature, each with its own comparative advantage.

Since the data on which the analysis is based comes from field survey, it is difficult to isolate spurious relationships from causal effects due to unobserved factors, measurement error as well as omitted variables. Some attempt was made to examine the extent to which membership to CBHISs could be weakly exogenous under certain assumptions which was supported by the appropriate test. One still wonders if instrumental variable methods would not be indicated in any case. The result from the simple probit model suggested that the effect of membership to

CBHISs has led to high degree of utilization of health services and helped protect members from large and unforeseen catastrophic health related expenses. The results are extremely favorable to poor households than non-poor households. Similar study undertaken on Senegal using the regression approach more or less reached at the same conclusion (Jutting, 2003).

The matching estimator, which does not rely on any functional form, has better predictive powers under the assumption that unobserved factors would not simultaneously influence the outcome and treatment variables (e.g. Barros and Machado, 2008, Johar, 2007)[5]. The result form these estimators are all consistent with the simple probit model in terms of validating the CBHISs as potent instrument for health service delivery and protection of households form consumption risk. As a scheme, the CBHISs helped the non-poor more in terms of higher utilization of health services and the poor in terms of protecting them from unforeseen health related expenses. This result has to be seen however with caution noting the underlying assumptions of each method. Often, matching estimators have been credited for robustness more than they actually deserve and rarely are capable of explaining why a program is working (Deaton, 2009)[6]. Given the specific conditions prevailing in Rwanda, it is not surprising to observe that households that were enrolled in CBHISs indeed reaped the benefits since the alternative is evidently worse. A sticking point in the whole debate is the flat premium that inherently discriminates against the poor. As the results indicated, the poor also tended to have low utilization rate of the health services reinforcing the inequity imbedded in the system. Fixing this may not be easy, but could have the potential of crowding out the poor from the health services market.

[5] Wooldridge (2009) showed that using instruments in matching estimators does more harm than good by introducing biases in the estimator.
[6] See also Heckman and Urzua (2009) and Imbens (2009) for an interesting debate on the topic.

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Table.1 Curative Health Care Seeking Behavior Entry in the Modern Health Care System among Beneficiaries and Non-Beneficiaries of Mutuelles Schemes By Socio-Economic Characteristics: EICV2 2005/2006		
Household or Individual Characteristics	Proportion (%) of sick individuals who sought care at a modern health care provider	
	Beneficiaries	Non-beneficiaries
	Proportion (%)	Proportion (%)
Self-perception of illness		
Not serious	**39.57**	**25.42**
Serious	**43.43**	**24.02**
Sex of individual		
Female	**36.75**	**22.59**
Male	**43.09**	**25.82**
Level of education		
No schooling	**40.00**	**20.16**
Primary incomplete	**42.33**	**25.81**
Primary complete	**43.43**	**25.48**
Vocational	**29.63**	**34.21**
Secondary school incomplete	**57.14**	**28.13**
Secondary complete	**75**	**63.64**
University and above		
Socio-economic status of household		
Poorest	**26.23**	**13.73**
Poor-Middle	**42.86**	**21.33**
Middle	**40.18**	**25.44**
Middle-Rich	**41.88**	**30.69**
Richest	**50.48**	**33.33**
Type of residence		
Urban	**44.0**	**29.7**
Rural	**40.7**	**23.21**
Province		
City of Kigali	**42.22**	**33.54**
Southern province	**44.34**	**23.10**
Western province	**34.56**	**25.71**
Northern province	**43.59**	**27.83**
Eastern province	**44.00**	**17.44**
Distance from nearest modern facility		
< 1 km	**47.83**	**25.00**
1-3 km	**42.70**	**29.47**
4-5 km	**37.11**	**18.72**
6-10 km	**42.86**	**28.26**
> 10 km	**29.27**	**15.74**
Total	**41.56**	**24.72**

Table .2: Probit regression of determinant of household participation in Mututelles (marginal effects)

Dependent variable is a dummy where household head is a member of Mutuelles

	coef	p-values in bracket
Sex of the head is male	0.055***	[0.00471]
Household size (<3 is base)		
3-4	0.081***	[0.00671]
5-7	0.106***	[0.000509]
>8	0.212***	[0.00640]
Age of head of household (<25 is base)		
25-34	0.071**	[0.0402]
35-49	0.073**	[0.0364]
>50	0.076**	[0.0376]
Level of education of head (base:illiterate)		
Primary incomplete	0.039**	[0.0451]
Primary complete	0.108***	[7.35e-06]
Vocational	0.153***	[0.000654]
Secondary school incomplete	0.142**	[0.0121]
Secondary complete	-0.081	[0.331]
University or above	-0.067	[0.686]
Consumption quintile (base:poorest)		
quintile2	0.016	[0.493]
quintile3	0.115***	[1.48e-06]
quintile4	0.113***	[9.31e-06]
Richest	0.125***	[0.000159]
Sector of activity of head (base: agriculture)		
Industry	0.001	[0.958]
Services	0.003	[0.905]
Distance to nearest health center (<1 km is base)		
1-4	0.041	[0.240]
4-7	0.021	[0.516]
7-10	0.018	[0.683]
>10	0.027	[0.478]
Geographic dummies (distrct 1 is base)		
Gasabo	0.08	[0.382]
Kicukiro	0.011	[0.866]
Nyanza	-0.049	[0.446]
Gisagara	0.021	[0.753]
Nyaruguru	-0.037	[0.549]
Huye	0.021	[0.770]
Nyamagabe	0.119*	[0.0905]
Ruhango	0.06	[0.401]
Muhanga	0.125*	[0.0651]
Kamonyi	0.255***	[0.000109]
Karongi	0.182**	[0.0131]
Rutsiro	0.221***	[0.00117]
Rubavu	0.175***	[0.00751]
Nyabihu	0.056	[0.410]
Ngororero	0.123*	[0.0533]
Rusizi	0.257***	[6.32e-05]
Nyamasheke	0.224***	[0.00106]
Rulindo	0.07	[0.328]
Gakenke	0.143**	[0.0372]
Musanze	0.121*	[0.0760]
Burera	0.086	[0.247]
Gicumbi	0.123*	[0.0526]
Rwamagana	0.175***	[0.00702]
Nyagatare	0.025	[0.722]
Gatsibo	-0.074	[0.280]
Kayonza	0.141**	[0.0383]
Kirehe	0.088	[0.215]
Pseudo-R2	0.0655	
Observations	4175	

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Determinants of entry into modern health-care system (marginal effects after probit)

Dummy if household is insured	0.159927***	[2.58e-05]
Age	-0.00866	[0.425]
AGE2	0.000079	[0.535]
Household size	-0.00271	[0.775]
Dummy for Urban residence	-0.160843***	[0.00206]
SEX==Male	0.040933	[0.312]
Log of pecapita consumption	0.088167***	[0.000526]
Primary incomplete	0.063177	[0.139]
Primary complete	0.014136	[0.793]
Vocational	0.015687	[0.870]
Secondary school incomplete	0.022743	[0.832]
Secondary complete	0.455521*	[0.0734]
District dummies (district 1 is base)		
Gasabo	0.007279	[0.968]
Kicukiro	0.021318	[0.930]
Nyanza	-0.02536	[0.892]
Gisagara	0.042278	[0.825]
Nyaruguru	0.169507	[0.412]
Huye	0.283806	[0.141]
Nyamagabe	-0.00288	[0.986]
Ruhango	0.00264	[0.988]
Muhanga	0.049183	[0.797]
Kamonyi	0.070524	[0.739]
Karongi	0.080518	[0.687]
Rutsiro	0.000796	[0.997]
Rubavu	0.087038	[0.658]
Nyabihu	0.472798**	[0.0326]
Ngororero	-0.17556	[0.134]
Rusizi	-0.03787	[0.823]
Nyamasheke	0.003997	[0.982]
Rulindo	0.225909	[0.303]
Gakenke	0.316679	[0.150]
Musanze	0.122391	[0.549]
Burera	0.239884	[0.306]
Gicumbi	-0.01092	[0.949]
Rwamagana	0.166379	[0.432]
Nyagatare	0.020054	[0.912]
Gatsibo	-0.07617	[0.620]
Kayonza	-0.09588	[0.516]
Kirehe	-0.08902	[0.561]
Ngoma	0.06514	[0.724]
Bugesera	-0.01371	[0.940]
Dummy if household head is seriously ill	0.021156	[0.530]
Dummy if household head is disabled	0.036345	[0.666]
Household head has land certificate	0.037284	[0.319]
Pseudo R2	0.113	
Observations	783	

*** p<0.01, ** p<0.05, * p<0.1

+University and above dropped due to collinearity.

Table 4: Marginal effects of membership to CBIs on selected variables: simple probit

	Coefficient	p-value	Weak-exogenity test (p-values)
Utilization of modern health care (households that reported sick)	.1599***	[0.000]	0.3828
Utilization of modern health care among the insured poor	.1714***	[0.001]	0.7052
Utilization of modern health care among the insured non-poor	.16756**	[0.006]	0.458
Out of pocket catastrophic health expenditure (all households)	-0.028***	[0.000]	0.993
Out of pocket catastrophic health expenditure (all households with positive health expenditure)	-.2923***	[0.000]	0.9127
Out of pocket catastrophic health expenditure (poor households with positive health expenditure)	-.3226***	[0.000]	0.795
Out of pocket catastrophic health expenditure (non-poor households with positive health expenditure)	-.2632***	[0.000]	0.3358

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Average treatment effect of community health insurance in Rwanda using simple matching estimator(ATE)

	Coefficient	p-value	Number of observations
Utilization of modern health care (households that reported sick)	0.146**	0.000	786
Utilization of modern health care (households that were poor and reported sick)	.085**	.046	397
Utilization of modern health care (households that were non-poor and reported sick)	0.269***	0.000	390
Out of pocket catastrophic health expenditure (all households with positive health expenditure)	-0.164***	.001	273
Out of pocket catastrophic health expenditure (poor households with positive health expenditure)	-.228**	.010	101
Out of pocket catastrophic health expenditure (non-poor households with positive health expenditure)	-.239**	0.001	101

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Average treatment effect of community health insurance in Rwanda among the treated using simple matching estimator (ATT)

	Coefficient	p-value	Number of observations
Utilization of modern health care (households that reported sick)	0.060	0.107	786
Utilization of modern health care (households that were poor and reported sick)	.052	0.282	397
Utilization of modern health care (households that were non-poor and reported sick)	0.207***	.000	390
Out of pocket catastrophic health expenditure (all households with positive health expenditure)	-.151***	.009	273
Out of pocket catastrophic health expenditure (poor households with positive health expenditure)	-.255***	.000	101
Out of pocket catastrophic health expenditure (non-poor households with positive health expenditure)	-.19760**	0.004	101

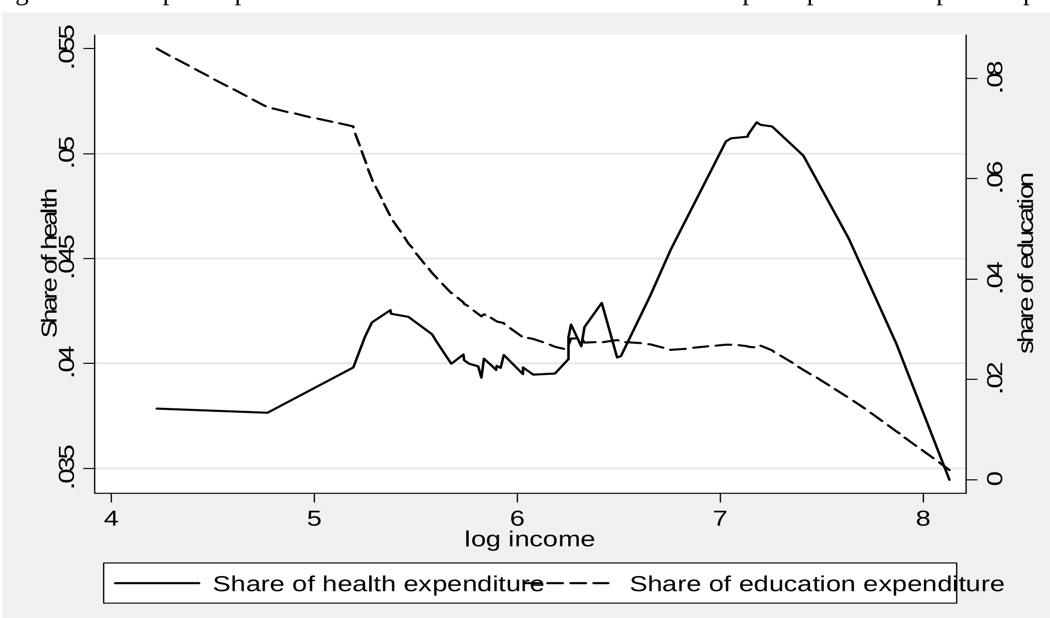
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Average treatment effect of community health insurance in Rwanda among the control group using simple matching estimator

	Coefficient	p-value	Number of observations
Utilization of modern health care (households that reported sick)	0.183***	.000	786
Utilization of modern health care (households that were poor and reported sick)	.098**	.036	397
Utilization of modern health care (households that were non-poor and reported sick)	0.298***	0.000	390
Out of pocket catastrophic health expenditure (all households with positive health expenditure)	-0.173**	.001	273
Out of pocket catastrophic health expenditure (poor households with positive health expenditure)	-0.228**	0.010	101
Out of pocket catastrophic health expenditure (non-poor households with positive health expenditure)	-.22519**	0.002	101

*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Per capita expenditure on health and education as a share of per capita consumption expenditure in Africa



Source: ADB International Comparison Project (2005)

Figure2: Per capita expenditure on health as a share of per capita consumption expenditure in Africa

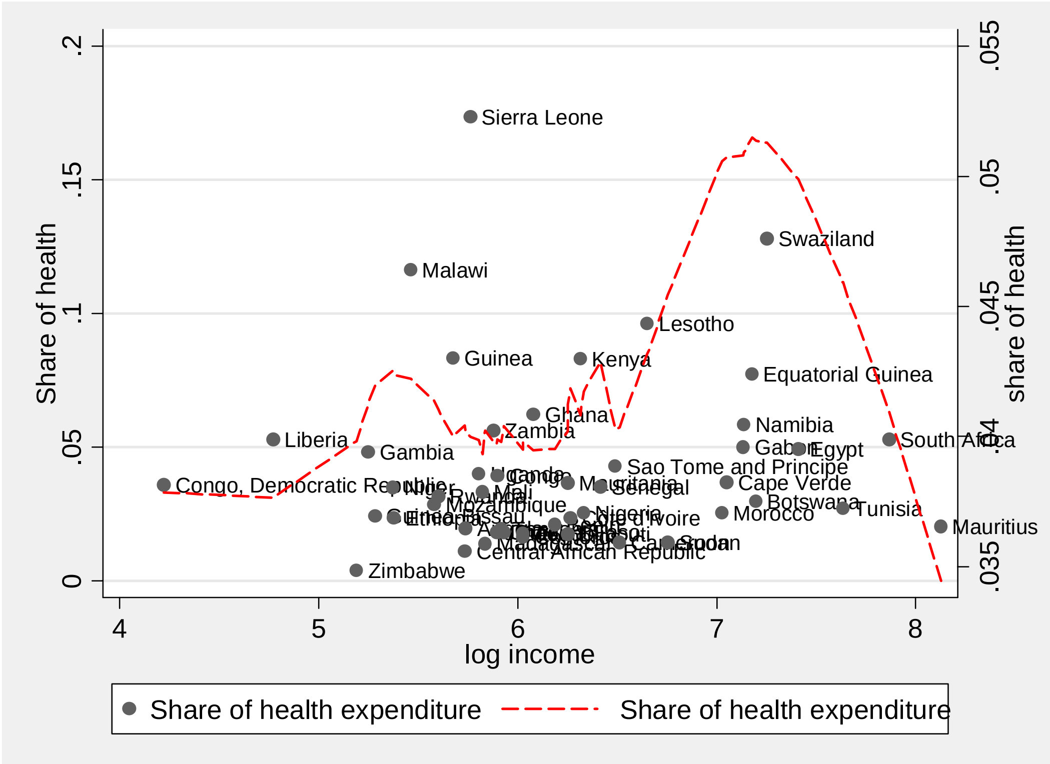


Figure 3: normalized out-of-pocket expenditure as a difference of total expenditure for households not enrolled in Mutuele

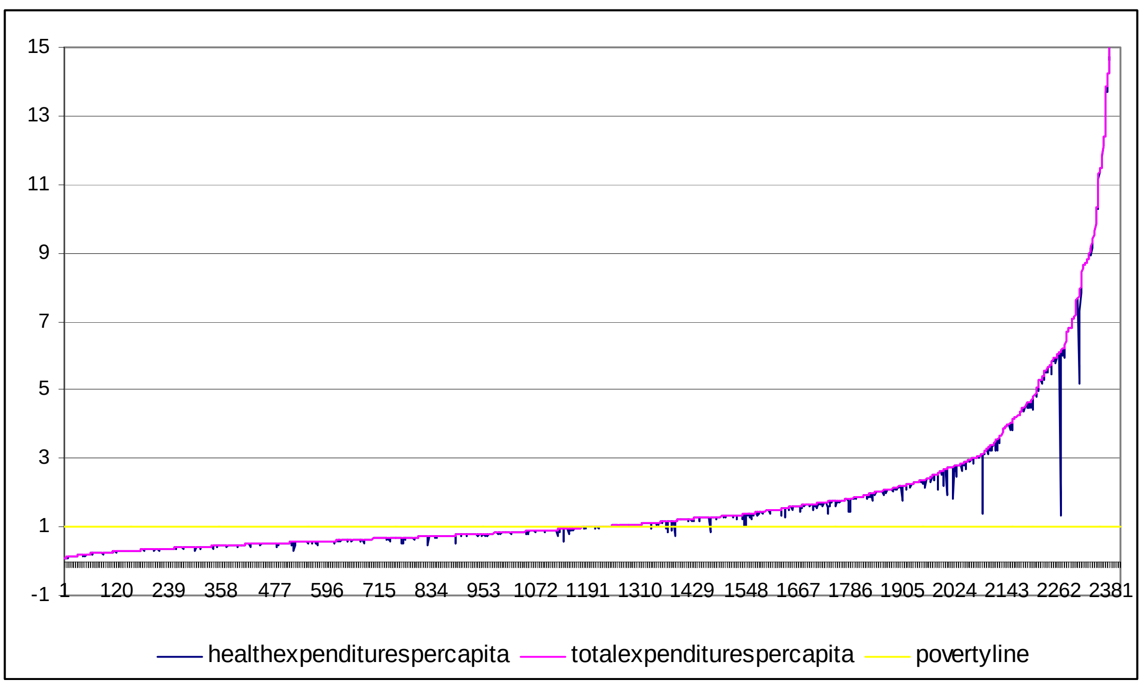


Figure 4: Out-of-pocket expenditure as a difference of total expenditure for households enrolled in Mutuele in poverty line units