The Policy Implications of Price Sensitivity of Demand for Health Insurance

Evidence from Community Based Health Insurance in Rwanda

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Abstract

In this study I use the implementation of a new premium subsidy scheme for the Community Based Health Insurance (CBHI) in Rwanda as a quasi-experiment to estimate the impact of premium subsidies on two policy relevant outcomes: insurance coverage and financial sustainability. Exploiting the variation in premium costs created by the policy reform, I estimate the price elasticity of insurance demand using a linear probability model with individual fixed effects. I show that the demand for health insurance is inelastic, but that the price sensitivity varies between different socioeconomic groups. I use the price elasticity estimates to simulate predicted take-up levels related to a number of different premium subsidy schemes. The results suggest that premium subsidies only have a modest effect on the take-up of insurance compared to non-subsidized premiums. Combining the price elasticity estimates with unique data on insurer costs, which enables me to take adverse selection into account, I simulate the financial sustainability of the insurance scheme related to the different subsidy schemes. Financial sustainability refers to the share of total insurer costs covered by insurance premiums. I estimate a positive slope of the average cost curve, which is consistent with adverse selection. My results suggest that the effects of adverse selection contribute to financially unsustainable insurance schemes.

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1 Introduction

In 2015 the UN General Assembly adopted Universal Health Coverage as part of the overall commitment to the Sustainable Development Goals (WHO 2015). In a developing country context, reaching the goal of universal health coverage often translates into a question of how to expand health insurance to the informal sector (Lagomarsino 2012). Community-Based Health Insurance (CBHI) has been adopted by many developing countries as a financing mechanism to extend health insurance to households in this sector (Aggarwal 2010 - India; Basaza et al. 2008 - Uganda; Fink et al. 2013 - Burkina Faso; Anagaw et al. 2015 - Ethiopia). This insurance scheme relies on prepaid membership premiums and offers financial security against health shocks by pooling risks and resources at the community level. So far enrollment has often been low, specifically among poor households (Gnawali et al. 2009; Yilma et al. 2015; Parmar et al. 2014). As a result, many countries have implemented premium subsidies as a policy tool to increase coverage.[1]

The main contribution of this paper is to provide evidence of the impact of premium subsidies on policy relevant outcomes such as insurance coverage and the financial sustainability of the CBHI scheme. First, I estimate the price sensitivity of demand for health insurance in the CBHI market. This is done in the context of Rwanda, a low-middle income country in Africa. Second, I use the estimated price sensitivity to predict enrollment rates, and subsequently premium income, for a number of alternative premium structures. In order to evaluate the financial sustainability associated with alternative subsidy schemes I consider the potential effects of adverse selection on insurer costs. To my knowledge, this is the first study to provide suggestive evidence of the financial cost of adverse selection in the voluntary health insurance market in the developing country context, as well as simulating policy outcomes related to alternative subsidy schemes.

In 2011 the Rwandan Government introduced a targeted premium subsidy in order to increase access to equitable healthcare and to improve the financial sustainability of the insurance scheme. After the policy change, households categorized as having low socioeconomic status received full premium subsidies whereas relatively wealthier households saw a price increase. The new premium policy was based on *Ubudehe*, a classification system developed by the Rwandan Government to categorize all house-

[1] Mexico (Bosch et al 2012); China (Wagstaff et al. 2012); and Ghana (Asuming et al 2017); Burkina Faso (Parmar et al. 2012) offer targeted premium subsidies to poor households

holds according to their socioeconomic status (Ministry of Health 2016). I explore this policy change as a quasi-experiment to identify the causal effect of price on the demand for insurance. Knowledge of the price sensitivity of demand can inform policy makers regarding the efficiency of premium subsidies as a policy tool to promote universal health insurance.

The results indicate that the demand for insurance is sensitive to price change, but not price elastic. An increase of the premium costs by Rwandan Franc (RwF) 1000 is associated with a decrease in the take-up of 9.16 percentage points (13.2% at the mean). This implies an average elasticity of -0.15. This is comparable to the price elasticity of demand for National Health Insurance Scheme in Ghana (-0.18) presented by Asuming et al. (2017), but is considerably lower than the estimated price elasticity of demand for preventative health products such as bed nets and deworming medicine (Dupas 2011; Kremer and Miguel (2007); Cohen and Dupas (2010)). Furthermore, the results show that the effect of a price increase varies with socioeconomic status: individuals living in female-headed or non-poor households are relatively more price sensitive compared to individuals residing in a wealthier household or a household headed by a man. The heterogeneous effects of a price increase on the demand for health insurance indicate that the introduction of premium costs affect some groups more than others.

Overall, the low estimated price elasticities indicate that premium subsidies are not an efficient policy tool for promoting take-up of insurance and universal health coverage. The low price-elasticity of demand implies that different premium subsidy schemes will not have large effects on overall insurance coverage. For example, I find that a decrease in the overall premium costs from RwF 3000 to RwF 1000 (USD 3.5 tio USD 1) would increase take-up from 68% to 77%. Additionally, a subsidy scheme that offers completely subsidized premiums for young children under 6 years old corresponds to a take-up of 69%, whereas a premium scheme without subsidies has a predicted coverage rate of 66%. Overall, the simulations indicate that insurance coverage remains relatively constant for different subsidy schemes.

In relation to the financial sustainability of the insurance scheme, I find some evidence of adverse selection. In a market with selection, the cost of providing insurance depends on the characteristics of the consumers (Stiglitz 1987). Changes to the price of insurance are predicted to affect the cost of providing insurance coverage as relatively healthier individuals drop out of the insurance as the premium costs increase.

Following the analysis presented by Einav et al. (2010), I provide suggestive evidence of the association between insurer costs and premium costs by estimating the average cost curve. A positive slope of the average cost curve indicates that the average insurer cost among enrolled households in a section increases as the average premium level increases, providing tentative support of adverse selection. Financial sustainability is calculated as the share of insurer cost that is covered by household premiums. The simulations indicate that the financial sustainability of alternative premium subsidies differ depending on whether the insurance market is adversely selected or not. In the absence of selection the range of coverage levels for the corresponding subsidy schemes are wider, suggesting that the financial coverage levels range between 0.3 - 0.9. Considering the adverse selection, the financial coverage reaches levels between 0.4 - 0.7 for the majority of subsidy schemes, that is, household premiums cover approximately 40-70% of the insurer costs. Not surprisingly, the difference between the level of financial coverage in the selection and no-selection scenarios increases as the premium levels deviate from the mean cost. The coverage levels for targeted premium schemes show similar levels of financial coverage. The differences in financial coverage occurs as a result of changes in the average insurer costs as individuals select into the insurance scheme as a result of changes in premium costs. Differences between average insurer costs in scenarios with and without adverse selection are indicative of the financial implications of selection. This is important knowledge that can inform policymakers on how adverse selection translates into future costs faced by the insurer.

The price elasticity is estimated using data from the Rwandan Integrated Household Living Conditions Survey (EICV) in 2010 and 2014. A sub-sample of the households in the 2010 data were tracked and interviewed again in 2014. These households constitute a panel, which is used for this investigation. The EICV data is nationally representative and contains information of family structure as well as health status, Ubudehe category, medical expenditure and insurance coverage. Furthermore, administrative cost data related to all CBHI health facilities enable me to estimate average insurer costs. These data contain information regarding enrollment rates, frequency of clinic and hospital visits, as well as healthcare expenditures and operational costs. This analysis relies on the variation in premium costs created by the introduction of a stratified premium structure in 2010, based on household socioeconomic status, to estimate the demand and cost curves. The new policy created variation in premium levels over time and across households, using targeted subsidies to households with relatively lower socioeconomic status.

Overall, this study makes several contributions to the literature. First, it adds to a relatively small and recent literature that seeks to evaluate the role of pricing in the take-up of health insurance in a developing country context (Thornton et al. 2010; Asuming et al. 2017; Capuno et al. 2016; Wagstaff et al. 2016).[2] This literature primarily relies on experimental variation in premium costs to identify the effect of short-term premium interventions on insurance take-up. To date, the empirical evidence is inconclusive. While some studies find no evidence that premium subsidies represent an efficient policy tool to increase take-up (Capuno et al. 2016; Wagstaff et al 2016),[3] others find relatively substantial impacts on enrollment (Thornton et al. 2010; Asuming et al. 2017).[4] I contribute to this literature by providing evidence from a nationwide policy intervention that resulted in variation in premium costs between households and across time. Furthermore, previous research argues that one-time external subsidies alone are often insufficient to encourage the take-up of health products (Kremer & Miguel 2007). This study explores the effects of a considerable and indefinite price change of a popular insurance scheme with a high enrollment rate. During 2011 67% of the target population were enrolled in the insurance scheme, which is a high number compared to enrollment rates in other countries such as Burkina Faso (6%), Ghana (38%) (Binagwaho et al. 2012), Laos (2%) (Alkenbrack et al. 2013).

Second, my results relate to the literature on adverse selection by providing evidence from the developing country context. The literature on adverse selection in the developing country context is fairly recent and inconclusive. While some studies find

[2]Another type of insurance that has received much attention in the literature is index-based crop insurance. Evidence from this literature indicates that demand for insurance is price sensitive, but that the insurance has low take-up rates at actually fair prices (Cole et al. 2012; Karlan 2014; Mobarak and Rosenzweig 2012)

[3]Capuno et al. (2016) find that a 50% premium subsidy in combination with increased access to information regarding the insurance led to a 3% increase in demand among informal worker households in the Philippines. Similarly, a 25% premium subsidy contributed to an increase in enrollment by 3.5 ppt (Wagstaff et al. 2016) in Vietnam

[4]Thornton et al. (2010) find that a $100 dollar 6-month premium subsidy, increased take-up of the Nicaraguan Social Security Insurance by approximately 30%. The results are supported by Asuming et al. (2017) who use a similar empirical strategy in Ghana to show that households who received a premium subsidy were 38 percentage points more likely to enroll in the national health insurance scheme. The results indicate that the demand for health insurance is highly price sensitive as enrollment doubles in response to a 1/3 price reduction. Levine et al. (2016) find that a premium subsidy of 80% contributes to an increase in enrollment in the SKY social health insurance in Cambodia. In contrast to previous studies, these results indicate that the demand is price elastic (-1.1). The Cambodian study deviates from the other papers by evaluating an insurance scheme that targets rural populations.

evidence of adverse selection (Wang et al. 2006; Zang and Wang 2008; Lammers and Wamerdam 2010), others do not (Kramer 2015; Nguyen and Knowles 2010; Banerjee, Duflo and Hornbeck 2014). A number of empirical strategies have been proposed. While some studies identify adverse selection by examining the correlation between ex-ante individual health risk and the likelihood of enrollment (Wang et al. 2006; Zhang and Wang 2008), others rely on the positive correlation test that measures the correlation between insurance coverage and individual risk (Chiappori and Salanie 2000). Previous literature on adverse selection in the developing country context is limited to only evaluating the relation between baseline health risk and insurance take-up (Wang et al. 2006; Zang and Wang 2008), and few studies consider the financial implications of adverse selection.

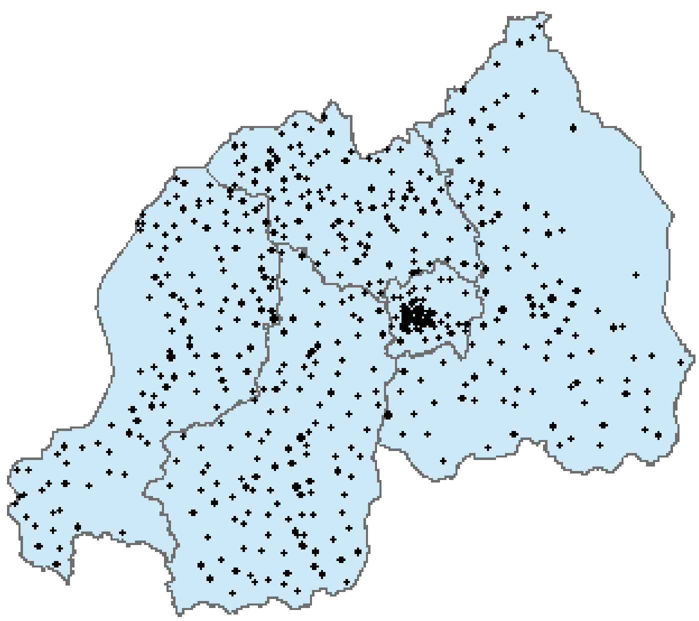
I test for adverse selection by evaluating whether the average insurer cost, that is the cost of insuring individuals, is correlated with changes in premium costs (Einav et al. 2010). Although this method has been frequently used to estimate the welfare effects of adverse selection in developed countries (Sacks 2017; Bundorf et al. 2012; Einav et al 2010b; Einav et al. 2010.), to the best of my knowledge, this is the first study that estimates the consequences of premium subsidies on the financial sustainability of health insurance in the developing country context. This method compliments the positive correlation test presented by Chiappori and Salanie (2000), by offering a test for adverse selection that controls for the presence of moral hazard (Einav et al. 2010).

This paper is organized as follows: Section 2 provides a description of the study context and the CBHI scheme in Rwanda. Section 3 presents the conceptual framework, whereas Section 4 presents the data and summary statistics. The empirical strategy is presented in Section 5, followed by a presentation of our results in Section 6. Section 7 provides the results from the policy simulations, and Section 8 includes some concluding remarks.

2 Community Based Health Insurance

Community-based health insurance (CBHI) was introduced in Rwanda in 1999 as a result of limited utilization and ability to pay for healthcare services among large segments of the population. The aim of the insurance system was to provide equitable access to quality health services among the population by providing the ability to pool health risks. CBHI was initially introduced as a pilot project in 3 districts (Kabgayi, Kabuyare and Byumba), encompassing 52 health centers and 3 hospitals. During this period, several additional districts developed insurance schemes similar to the governmental initiative. In 2004 the Rwandan Government developed a policy framework in order to homogenize the regional insurance schemes and to offer a national health insurance. During 2005, this scheme was expanded to all 30 districts in the country and the CBHI achieved national coverage. In response, enrollment increased drastically from 7% in 2003 to 74% by 2013 (Ministry of Health 2016). Figure 1 shows the distribution of health centers covered by the insurance scheme. The facilities are distributed all over the country with a high concentration of health centers in the capital of Kigali (Ministry of Health 2016).

Figure 1: Distribution of CBHI Health Centers in Rwanda



In conjunction with the standardization of the CBHI scheme, a uniform premium system was also developed and introduced. This premium required members to pay an individual annual premium of RwF 1000 (Rwnda Franc), corresponding to approximately USD 1.1 individual and per year. The premium level was set based on average insurer costs at the health centers, but did not cover costs associated with secondary level care such as district and national hospitals (Ministry of Health 2004). Due to financial barriers, the Rwandan Government decide to offer full premium subsidies to indigent households. In 2006, in conjunction with the implementation of the national policy, free premiums for the poor were formally put in place (Ministry of Health 2016). However, despite this targeted subsidy, the premium structure was considered strongly regressive and exclusive of the poor (Ministry of Health 2016).

In order to promote equal access to healthcare, in 2011, the flat-rate premium was replaced by a stratified premium system that targeted households with low socioeconomic status. The new premium system was based on *Ubudehe categories*, a socioeconomic classification system developed by the Ministry of Local Government. Under the Ubudehe system, the population was categorized into 6 categories reflective of their socioeconomic status. The Ubudehe system considers a wide range of socioeconomic factors including household nutrition, financial and non-financial assets, access to property, household livelihood and production capacity etc., with those in category one classified as living in abject poverty and households in category 6 classified as money rich (for further description of the Ubudehe classification see Table A5 in appendix).

As shown in Table1, the new premium structure required an annual individual premium of RwF 2000 (USD 2.4) for households in premium category 1, the lowest two Ubudehe groups 1 and 2. This premium is completely subsidized by the government. Ubudehe groups 3-4 are classified into CBHI premium category 2, paying a premium of RwF 3000 (USD 3.4) per individual and year. Households in the two highest Ubudehe groups, categories 6 and 6, are placed in premium category 3, with a premium of RwF 7000 (USD 7.9) per year.[5] Despite the individual premium structure of the CBHI, each individual in the household face the same premium level. Overall, the policy change resulted in an increase in premium costs among beneficiary households. While the number of beneficiaries who received fully subsidized premiums increased, households in the two higher premium categories saw relatively sharp price increases following the policy change.

Ubudehe was first introduced by the Rwandan Government in 2001. Hence the classification of households into Ubudehe groups was not developed with the aim of determining the premium costs for the CBHI, since the categorization system was in place well before the introduction of the stratified premium system in 2011. As a result, households are not likely to sort into specific Ubudehe categories in order to receive lower premium costs. However, technically households did have the opportunity to change categories in order to lower the cost of health insurance. Due to the complexity

[5] tableA6 shows that premium costs increased from approximately 1.7% of household consumption on average among households in Ubudehe category 3, to 4.9% on average after the policy change.

of the Ubudehe categorization, in order to change classifications households would have to change across several wealth-related factors such as main livelihood, nutrition and children's schooling.

Table 1: Ubudehe and Premium Categories

Ubudehe	CBHI premium	Premium before 2011	Premium after 2011
Ubudehe 1 (abject poverty) Ubudehe 2 (very poor)	category 1	0 or 1000	0
Ubudehe 3 (poor) Ubudehe 4 (resourceful poor)	category 2	1000	3000
Ubudehe 5 (food rich) Ubudehe 6 (money rich)	category 3	1000	7000

In addition to the premium, members pay a flat co-payment fee of RwF 200 each time they visit a health center, as well as a co-payment of 10% of the total hospital bill (Ministry of Health 2016). The new premium schedule was meant to increase the financial sustainability by increasing premium revenues and reducing dependence on external subsidies. In addition to premium and member co-payments, governmental funds and external resources, primarily from the US Government and the Global Fund, represent important sources of income for the insurance scheme. Furthermore, since 2008 the Rwandan Government has mandated that other insurance companies provide 1% of their income to CBHI (Ministry of Health 2016).

CBHI beneficiaries are entitled to a predefined package of healthcare services known as the Minimum Package of Activities (MAP). Those are provided at all levels of the public healthcare delivery system: health centers, district hospitals and referral hospitals. The scheme is mainly financed through member premiums that represent approximately 66% of the total budget (Ministry of Health 2016). This revenue is split almost equally between the health centers at the section level, and the hospital claims at the district level. Approximately 10% of the funds that are directed to the district are forwarded to a national risk-fund to cover services at the referral hospital level. The Rwandan government represents the second largest source of funding (14%), primarily covering the contributions of indigent members. The Global fund covers approximately 10% of the total budget.

3 Conceptual Framework

The following section develops a model of supply and demand in a market with a single, fixed product available, closely following Einav et al (2010). Their model describes a situation where individuals are allowed to choose from two different insurance contracts, one with a higher coverage and one with relatively low coverage. This set-up is simplified by assuming that the contract with low coverage represents having no insurance. Let, $L = \{NoCBHI, CBHI\}$ indicate these alternatives and let the relative price of CBHI be denoted by p^{CBHI}. The coverage of the insurance contract is taken as given, only allowing for variations in price between households.

Assume a population that is distributed according to $F(x_{ijk}, \varepsilon_{ijk})$, where x_{ijk} denotes observed individual (i), household (j) and village (k) characteristics and ε_{ijk} denotes unobserved characteristics that encompass, for instance, taste/preferences towards insurance, the degree of risk aversion, and underlying health risk. A key feature of the approach is that it does not impose any restrictions on F (Einav et al. 2010). Consumer utility from buying contract $CBHI$ and $NoCBHI$ is denoted $v^{CBHI}(x_{ijk}, \varepsilon_{ijk}, p^{CBHI})$ and $v^{NoCBHI}(x_{ijk}, \varepsilon_{ijk})$.

It is assumed that $v^{CBHI}(x_{ijk}, \varepsilon_{ijk}, p^{CBHI} = 0) \geq v^{NoCBHI}(x_{ijk}, \varepsilon_{ijk})$.

All individuals have an expected cost $c(x_{ijk}, \varepsilon_{ijk})$ that describes the expected cost of providing insurance coverage for the insurer, given the insurance contract. This does not include out-of-pocket payments, but only describes the cost each enrolled individual incurs on the insurer. The cost varies among individuals depending on individual observable and unobservable characteristics, such as age, sex, as well as individual preferences for healthcare and risk. The costs does not depend on the chosen contract.

3.1 Demand

Each individual makes a discrete choice of whether to buy insurance or not. Individual i chooses to buy insurance if and only if $v^{CBHI}(x_{ijk}, \varepsilon_{ijk}, p_j^{CBHI}) \geq v^{NoCBHI}(x_{ijk}, \varepsilon_{ijk})$. In line with Einav et al. (2010) I define $\pi(x_{ijk}, \varepsilon_{ijk}) = max\{p : v^{CBHI}(x_{ijk}, \varepsilon_{ijk}, p) \geq v^{NoCBHI}(x_{ijk}, \varepsilon_{ijk})\}$, as the highest price an individual is willing to pay for the insurance. This represents individual willingness-to-pay for insurance. Following this notification, aggregate demand for health insurance could be expressed by:

$$D(p) = \int 1\pi(x_{ijk}, \varepsilon_{ijk}) \geq p_j^{CBHI}\} dF(x_{ijk}, \varepsilon_{ijk}) \tag{1}$$

3.2 Costs

At the insurer level, the average cost is determined by the characteristics of individuals who decide to enroll in the insurance. Each individual has an expected cost $c((x_{ijk}, \varepsilon_{ijk})$ that describes the expected cost for the insurer of providing coverage to an individual of type$(x_{ijk}, \varepsilon_{ijk})$. At the aggregate level, and given a population with individual characteristics distributed according to $F(x_{ijk}, \varepsilon_{ijk})$, the average cost is given by:

$$AC(p) = \frac{1}{D(p)} \int c(x_{ijk}, \varepsilon_{ijk}) 1\{\pi(x_{ijk}, \varepsilon_{ijk}) \geq p_j^{CBHI}\} dF(x_{ijk}, \varepsilon_{ijk}) \tag{2}$$

A positive correlation between $c(x_{ijk}, \varepsilon_{ijk})$ and $\pi(x_{ijk}, \varepsilon_{ijk}$ will result in an $AC(p)$ higher than the unconditional $c(x_{ijk}, \varepsilon_{ijk})$. The marginal cost (MC) curve can be recovered from the AC curve. The MC curve describes the expected costs of individuals who are indifferent between enrolling in the insurance and not at p:

$$MC(p) = E[c(x_{kij}, \varepsilon_{ijk}) | \pi(x_{ijk}, \varepsilon_{ijk}) = p_j^{CBHI}] \tag{3}$$

A downward sloping marginal cost curve indicates that individuals with a relatively higher willingness to pay for the insurance also have the highest expected cost to the insurer. If $c(x_{ijk}, \varepsilon_{ijk})$ is positively correlated with $\pi(x_{ijk}, \varepsilon_{ijk})$, $AC(p)$ will be higher than the unconditional average cost in the population, which indicates adverse selection.

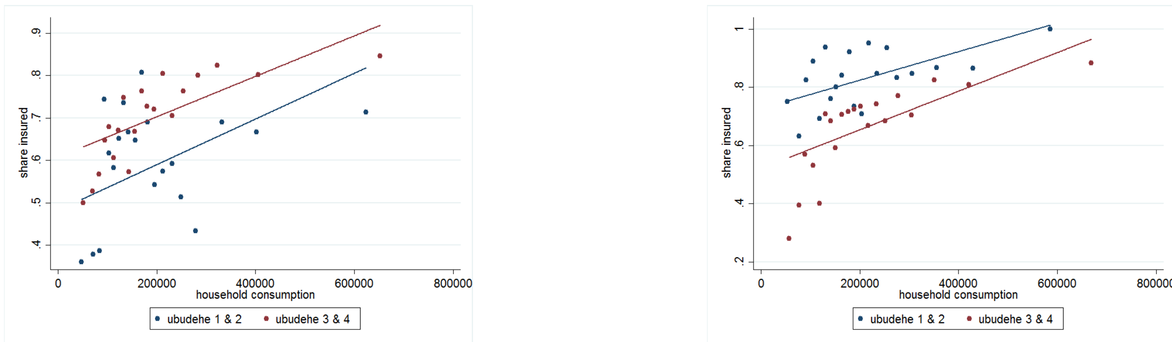
4 Data

This analysis is primarily based on data from the Rwandan Integrated Household Living Conditions Survey (EICV). The EICV is a regular household survey, representative at the national level. This analysis uses two survey rounds conducted in 2011 (EICV3) and 2014 (EICV4). A sub-sample of households in the EICV3 data were tracked and interviewed again in 2014. These households constitute a panel comprising 1604 households and 13,224 household members. 1326 households were included in this study, resulting in a panel of 5488 individuals.[6] The data contains information on household demographics, socio-economic characteristics, as well as wealth, employment and health conditions. The EICV data does not contain information regarding premium costs, but classifies all households into a specific socioeconomic category, or Ubudehe category. Due to the structure of the new premium scheme, information on household Ubudehe category provides information about the premiums that each household face, even those who are not enrolled in the insurance scheme.

Figure 2 shows the average enrollment rates for individuals in premium category 1 and 2, using household consumption as a running variable. The figure on the left illustrates enrollment in 2010, before the policy change, whereas the figure on the right describes enrollment in 2014, after the new premium policy was implemented. Each dot represents the average enrollment rate within a 5% consumption-bin. The results indicate a positive relation between enrollment levels and consumption for both categories, both before and after the premium change. However, while Ubudehe groups 3 and 4 (premium category 2 in the CBHI premium structure) showed higher enrollment in relation to lower Ubudehe categories at all consumption levels prior to the new premium system, the relation is reversed after the policy change, that is, there is a shift in the demand curves after the policy change. The results suggest that the policy induced price increase had a negative effect on demand, suggestive of a negative price elasticity. Furthermore, the results indicate that while the relation between enrollment and consumption is similar between the groups in 2011, the correlation is relatively stronger for Ubudehe group 3 and 4 after the policy intervention. The figures provide suggestive evidence of a negative association between premium costs and demand for health insurance.

[6] Households with at least one individual who was coded as if they had changed sex during the period, or had age discrepancies of more than 6 years during the study period, were excluded from the study in order to ensure the identification of the households in the panel. 84 households were excluded due to age whereas 55 households were excluded due to the change of sex of at least one family member.

Figure 2: Enrollment shares per consumption group, pre- and post policy change



Pre-policy, 2011 Post-policy, 2014

Descriptive baseline statistics are presented in Table A2. The first column shows that approximately 67% of the population in Rwanda were enrolled in the CBHI scheme in 2010. This insurance coverage is high compared to other countries with similar insurance schemes: National Health Insurance Scheme in Ghana 40% in 2014 (World Bank 2017), CBHI in Ethiopia 8% and National Health Insurance Scheme in Nigeria 3% (Chemoini 2018), or Vietnam Social Security 42% (Lagomarsino 2012). Furthermore, nearly 30% of the sample had access to piped water and 75% to improved sanitation such as toilet or latrines with slab. Approximately every second individual state that they work and 85% live in a rural household. On average, individuals are 23 years old and live in a household with on average 5 household members. 53% of the population are women and almost 50% of all individuals live in a household that is categorized as poor according to the national poverty line. A large majority of households, 88%, are classified as Ubudehe group 2 and 3, with approximately 64% of all households being classified as Ubudehe poverty group 3 and 23% placed in category 2.

Column 2 and 3 present descriptive statistics for insured and uninsured individuals respectively. Uninsured individuals are less likely to work, but more likely to work as a salaried worker.[7] Furthermore, uninsured individuals tend to have larger families, be younger and live in households with lower consumption compared to insured individuals. Additionally, households with access to improved sanitation (latrines and toilets) and protected water sources, and those who are considered poor according to measures

[7]It is important to note that all households with at least one household member enrolled in another health insurance plan have been excluded from this analysis. Consequently, it is unlikely that the low enrollment rates among salaried workers reflects a situation where this group of workers are offered alternative insurance schemes through their employers.

of household consumption (poor), are over-represented among the uninsured households. Furthermore, the results indicate that uninsured individuals are more likely to belong to the lower Ubudehe groups. Households in Ubudehe group 2 are more likely to be uninsured whereas households in Ubudege group 3 are overrepresented among the enrolled. Despite the significant differences between insured and uninsured individuals, it is important to note that there is no significant difference between the two groups in terms of health related outcomes. Individual health status is proxied by an indicator that takes the value one if an individual stated that he or she had been sick during the 2 weeks prior to the survey, and an indicator that takes the value one if an individual has a disability such as being death or blind.

The cost analysis is based on a unique data set provided by the Ministry of Health in Rwanda. The data provide a register of the complete costs of running the CBHI in Rwanda, and the cost of providing medical coverage for all enrolled individuals. The cost data is provided at the sector level, that is, each observation describes the complete costs for each health sector in the country. A health sector is an administrative entity that approximates the take-up area of a health clinic.

The total insurer costs include a number of expenditure posts: health consultations and hospitalization, operational costs, as well as reimbursement to health clinics and to the risk pool in order to cover hospital claims. Table 2 describes averages expenditures per beneficiary. Reimbursements to health clinics for their services represent the largest expenditures within the CBHI, followed by payments to the district risk pool and operational costs. On average, an individual enrolled in the CBHI scheme generates a cost of RwF 3526 during one year (approximately USD 4.). This cost represents approximately the premium cost of RwF3000 payed by individuals in premium category 2, as well as it gives an indication of the level of subsidy provided to households in premium category 1. Households in this category receive completely subsidized premium, generating a subsidy cost of approximately RwF 3500 per individual.

Table 2: Insurer costs, avg. 2013-2014

Expenditure	N	Mean	Sd	Min	Max
Health consultations	306	881.52	356.35	180.08	2315.54
Hospitalization	306	94.58	86.23	1.14	579.49
Reimbursements	306	1318.76	465.32	393.62	3951.68
District risk pool	306	1098.26	398.07	223.49	2846.67
Operational costs	306	132.93	84.61	8.930	621.86
Total costs	306	3526.07	829.13	1241.66	6839.56

5 Empirical Strategy

Table 3 shows how the Ubudehe classification relates to the premium categories of the CBHI scheme after the introduction of the stratified premium scheme. The introduction of the stratified premium structure created large differences in premium cost across different Ubudehe categories. Four categories of beneficiary households can be identified: 1) households that received no price increase 2) households that received a considerable increase in premiums (RwF 0 to RwF 3000) 3) households that saw a price reduction (RwF1000 to RwF 0), 4) households that are relatively better off and who received a sharp price increase (RwF 1000 to RwF 7000) (Ministry of Health 2016). The policy change resulted in a significant difference in premium costs between households in poverty groups 2 and 3. At the same time, the Ubudehe classifications suggest that these households have potentially similar wealth levels. The Health Ministry admits that the Ubudehe categorization is not always entirely accurate, and that the classification between some categories to some extent is random. This is especially true for households in Ubudehe Category 2 and 3. Consequently, some households in CBHI category 2 are likely to be richer than expected, while some households in CBHI category 1 might be poorer than expected (MSH 2016). The Ubudehe classification was only relevant for pricing of CBHI after the introduction of the new premium structure.

According to CBHI policy rules, the insurance scheme applied a flat individual premium of RwF 1000 per year prior to the introduction of the new premium structure. However, administrative documents state that the poorest households received completely subsidized premiums even before the policy change. The EICV data does not contain any information regarding the premium subsidies prior to the policy change, however, subsidies were defined based on the national poverty line that categorize households according to their consumption level (Ministry of Health 2016; Lu et al. 2012). I define indigent households using a measure based on household Ubudehe category and the national poverty measure prior to 2011. We categorize households who belonged to Ubudehe group 1 in 2010, and at the same time were classified as extremely poor according to the national poverty line, as indigent. These households received completely subsidized premiums before the policy change. Table A1 shows the relation between the income poverty measure and the poverty measure based on household consumption level. Errors to the estimation of premium costs before the new policy introduction could potentially result in an over- or under estimation of the price sensitivity. I run a number of sensitivity checks using alternative definitions of indigent households to make sure that the estimated price sensitivity is robust to different definitions of fully subsidized households prior to the policy change. This analysis is presented in Appendix Table A4.

Table 3: Premium Categories

Ubudehe	Share	CBHI premium	Premium before 2011	Premium after 2011
Ubudehe 1 (abject poverty)	1.41 %	category 1	0 or 1000 (USD 1.1)	0
Ubudehe 2 (very poor)	23.30 %			
Ubudehe 3 (poor)	64.44 %	category 2	1000 (USD 1.1)	3000 (USD 3.4)
Ubudehe 4 (resourceful poor)	10.33 %			
Ubudehe 5 (food rich)	0.34 %	category 3	1000	7000 (USD 7.9)
Ubudehe 6 (money rich)	0.18 %			

To identify the price elasticity of insurance demand and claims, the analysis exploits the variation in premium costs created by the introduction of the stratified premium system in the Rwandan CBHI in 2011. This variation in price is used in a difference-in-difference approach with intensity treatment. I estimate equation 4 using a linear probability model (LPM) with individual fixed effects (FE). The FE model explores the within subject variation in price that was created by the policy. As discussed in the previous section, some households saw no price change after the policy change, whereas others faced an increase in individual premium costs from RwF 1000 to RwF 3000 or RwF 7000, depending on household wealth level. Additionally, a small share of the households that were fully subsidized prior to the policy intervention received premium costs of RwF 1000 or RwF 3000 with the new premium scheme.

I estimate the following specification:

$$\Pr(CBHI_{ijkt} = 1 | X_{ijkt}, \mu_i, p_{jt}^{CBHI}, \gamma_t) = \beta_1 p_{jt}^{CBHI} + X_{ijkt}\beta_2 + \gamma_t + \mu_i \tag{4}$$

where i indexes individual, j household, k sector and t time periods 2010, 2014. $CBHI_{ijkt}$ indicates individual i's insurance status in time period t. The treatment variable measures individual premium cost, determined at household level, and indicated by p_{jt}^{CBHI}. The treatment is the individual premium level of each household at a specific time, before and after the policy change. X_{it} is a vector of individual time-variant factors that are potentially correlated with the outcome, such as age, labor- and health status, wealth level etc. μ_i are individual fixed effects, controlling for individual characteristics that vary across individuals, but are constant over time. Importantly, individual fixed effects control for time-invariant differences in individual health risk which is likely to be correlated with insurance status, as well as premium costs as described earlier.

In all specifications, standard errors are clustered at the household level. The LPM assumes a linear relation between price and insurance enrollment.

Variation in insurer costs between different health sections in the CBHI are used to estimate the cost curve. The association between premium levels and insurer costs are identified based on variation in the coss-section. The analysis relies on differences in the composition of households across the different premium categories in each health section to create variation in average premium costs across sections. Sections with a high share of completely subsidized households will have a lower average premium level in relation to sections with a relatively larger share of households in premium category 2 and 3.

The average cost curve is estimated using OLS, assuming that insurer costs are linear in price. The cost equation is estimated on enrolled individuals.

$$c_{ijk} = \delta_0 + \delta_1 p_{jk}^{CBHI} + \boldsymbol{X}_{ijk}\delta_3 + \sigma_{ijk} \tag{5}$$

where c_{ijk} is calculated as an average of the total costs for medical consultations, hospitalizations, medicine and ambulance use, as well as administrative costs, per enrolled individual in each health sector. δ_1 measures the effect of a price increase on average insurer costs, X_{ijk} is a vector of sector characteristics. The sign of δ_1 is informative of the presence and nature of selection in the health insurance market. A positive relationship between individual insurer cost and the premium indicates adverse selection as individuals endogenously exit and enter the market as a result of the price change. Individuals with relatively better health status will exit the insurance scheme as premium levels increase and exceed the expected healthcare expenditure (Sacks 2017; Einav et al. 2010).

My cost data is aggregated at the health sector level, which requires me to aggregate the cost curve accordingly:

$$c_k = \sum_{ij} \{\delta_0 + \delta_1 p_{jk}^{CBHI} + \boldsymbol{X}_{ijk}\delta_3 + \sigma_{ijk}\} \tag{6}$$

5.1 Threats to Identification

The identification strategy in this paper relies on the assumption that unobservable factors that are simultaneously correlated with insurance enrollment and key predictors are time-invariant. The fixed effects specification relies on individual fixed effects that captures time-invariant unobservable characteristics such as preferences, risk aversion and underlying health characteristics. Furthermore, the specification controls for a set of observable characteristics. Given this strategy the potential threats to identification are caused by omitted time-varying factors that are simultaneously correlated with insurance enrollment and key predictors. Thus the results are robust to any possible confounder as long as it does not violate the parallel trends assumption. These variables could for example be changes in individual health status or economic conditions that would affect willingness to pay for insurance. The assumption of unconfoundedness is not testable. The remaining portion of this section will discuss potential scenarios that could give rise to endogeneity, and its effect on the presented estimates in this paper.

As discussed earlier, due to the Ubudehe-based structure of the CBHI premium structure, households in different premium categories will differ with respect to to a number of socioeconomic factors. Households in premium category 1 are relatively poor and have a lower socioeconomic status on average compared to households in premium category 2. Individuals with low health status are likely to have a higher willingness to pay for insurance as a result of higher expected healthcare expenditure. At the same time, these individuals are also more likely to be categorized in Ubudehe group 1 or

2. The individual fixed effects model control for time-invariant differences between the different premium groups. However, differences in socioeconomic status could imply that households in the lower Ubudehe groups are less resilient to health shocks than households in higher Ubudehe groups. In this context, the effects of an adverse health shock could vary between the insurance groups. If the health shock coincides with the introduction of the premium policy, this creates a negative correlation between premium change and the idiosyncratic error term, $E(\varepsilon_{ijkt}, p_{jkt}^{CBHI}) < 0$. This would result in overstated estimates of the price sensitivity. Additionally, production shocks that are concentrated to rural areas could give rise to endogeneity if households in the lower Ubudehe groups are concentrated in rural areas. Similar to above, if the shock coincided with the new premium policy, it could result in biased estimates of the price sensitivity.

Another threat to identification would be posed by other policy interventions that exclusively target individuals in premium category 1, and that directly or indirectly affect the health status of the targeted population. If the policy coincided with the premium policy change in the CBHI market, this would result in an downward bias of the price sensitivity estimates since households who received completely subsidized premiums after the policy change, at the same time would decrease their willingness to pay for insurance as a result of improved health status and lower expected health costs, that is, $E(\varepsilon_{ijkt}, p_{jt}^{CBHI}) > 0$.

The Rwandan Health Sector Strategic Plan (III) provides strategic guidance to the health sector. The strategic plan points out a number of health-related focus areas, such as malaria, water and sanitation, and HIV. As shown in Table 4, and in line with the national development policies, access to piped water and improved sanitary services has increased significantly during the study period, predominantly in the lower Ubudehe groups. The empirical strategy adjusts for changes in access by including indicators for household main water service and toilet facility. Besides controlling for household access to these services, these proxy variables also adjust for potential changes in unobservable factors that are correlated with improved water and sanitation services.

Malaria represents another key focal area in the Health Sector Strategic Plan (2012-2018). According to WHO, malaria is the leading cause of morbidity and mortality in Rwanda, responsible for up to 50% of all outpatient visits (WHO 2018; citation). Descriptive statistics in Table A12 confirm that malaria is stated as one of the main causes for having been sick during the last weeks (17% prior to the policy change and 25.6 % afterwards). It is important to note that the causes for illness are likely to vary over time due to changes in weather, which may result in variation in the main sicknesses stated. Governmental policy interventions related to malaria are coordinated and guided by the Malaria Strategic Plan (MSP). The overall target of the MSP is to eliminate malaria through a number of defined strategies. In 2011, Rwanda achieved universal coverage of insecticide-treated mosquito nets for all age groups. Since then, bed nets are routinely distributed across the country through antenatal clinics, programs for immunization clinics and boarding schools (Rwanda Malaria Operational Plan 2017). Besides impregnated bed nets, the MSP contains policy interventions such as indoor residual spraying, malaria reduction in pregnancy and health system strengthening and capacity building (Rwanda Malaria Operational Plan 2017). The documents reveal that the Rwandan Government has launched a number of policies with the aim of eradicating malaria during the study period. These policies are likely to have positive effects on individual health status, and thereby also individual willingness to pay for the health insurance. In line with previous discussions, this could result in biased estimates if these policies specifically targeted households in the lower Ubudehe groups who also received fully subsidized premiums for the CBHI. One such scenario would be the targeted distribution of bed nets to the two lowest Ubudehe groups, which could create a positive impact on health status that is limited to these Ubudehe groups. This would result in an conservative estimation of the price sensitivity of demand for health insurance. However, the MSP indicates that the majority of malaria policies are universal and target the entire population, regardless of Ubudehe category. For example, indoor residual spraying targets individuals who live in malaria intensive areas, regardless of Ubudehe group.

Another plausible source of endogeneity is reverse causality, which contributes to biased OLS estimators as a result of correlation between the explanatory variables and the regression error term, $E(\varepsilon_{ijkt}, X_{ijkt}) \neq 0$. The majority of the potential channels of impact of the dependent variable on the explanatory variables are likely to be of importance in the medium and long run. For example, increased access to health insurance could affect individual health status and labor productivity positively, which, in turn, would affect household premium costs through improved socioeconomic status and ubudehe group. However, it is important to note that the ubudehe classification is defined based on a number of socioeconomic indicators such as labor productivity, access to land and housing, nutrition and assets. Despite the possibility that improved health and labor productivity could affect some of the ubudehe indicators in the short run, other factors such as access to land and housing are more likely to change in the medium-long run. This study covers a period of 4 years, 2010-2014.

In relation to the insurance premium p_{jk}^{CBHI}, the key explanatory variable, insurance status could affect premium costs if improved access to insurance contribute to improved health and labor productivity and, subsequently, household socioeconomic status. In this scenario, insurance status would affect the premium cost.

Regarding potential bias in the cost estimations, the effect of price on insurer costs is identified by using variation in the average premium costs between health sections in the coss-section. Consequently, the analysis does not rely on any variation in price over time. According to Ubudehe classification and insurance regulation, households in sections with relatively lower premiums will have a lower socioeconomic status on average compared to households in other sections. The cost of insuring individuals is likely to be affected by overall household socioeconomic status, that is, the variation in premium costs is likely to be endogenous. As a result, the relation between pricing and socioeconomic status could result in biased estimates of the effect of price on insurer costs. I control for a number of section characteristics that could be relevant in explaining variations in premium costs and claims across sections.

5.2 Differences between groups

The difference-in-difference analysis hinges upon the assumption of parallel trends, which posits that the average change in the control group represents the counterfactual change in the treatment group if there were no treatment. Table A3 provides summary statistics for the different premium categories. As expected, and according to the premium structure, the results indicate that there are large differences in individual and household characteristics between the different categories, confirming the correlation between Ubudehe classification and premium category.

In order to further evaluate the parallel assumption, I analyze households from Ubudehe group 2 and 3. As mentioned earlier, approximately 88% of the population are categorized in Ubudehe group 2 and 3. By restricting the sample it is plausible to look at the two groups as two treatment groups that face different treatment intensity. Despite the perceived socioeconomic similarities between the two groups, there is a sharp difference in the implications of the new premium policy: while households in the lower ubuedhe category received completely subsidized premiums, premium levels among households in category 3 increased to RwF 3000.[8] I refer to individuals in Ubudehe group 3 as treatment group whereas households in Ubudehe group 2 are referred to as the control group.

Table 4 presents descriptive statistics for households in Ubudehe group 2 and 3. First, I look at balancing tables for the treatment and control group. I find several significant differences between the two groups when I test the hypothesis of equality using t-tests. On average, households in Ubudehe group 2 have lower socioeconomic status compared to households in group 3: they are less likely to have access to piped water, to have a flush toilet or latrine with solid slab, they have significantly lower household consumption, and they are less likely to have salaried employment. Importantly there is a significant difference between the groups in health-related factors, that is, households in the lower Ubudehe category are more likely to report having experienced a health issue during the last 2 weeks prior to the survey or to have a disability. Furthermore, households in Ubudehe group 2 need to travel 0.4 hours longer on average in order to reach the nearest hospital. The descriptive statistics verify the accuracy of the Ubudehe classification system as an instrument to categorize households according to their socioeconomic status by revealing systematic differences between the two categories. However, the identification strategy allows for different levels, as long as the two groups are on similar pre-treatment trends. This is the parallel trend assumption.

In Table 4, columns 5 - 7 I present changes in individual and household characteristics over time. Column 7 shows the difference-in-difference estimates, revealing whether the detected differences in characteristics between the two groups persist over time or whether it is possible to observe differences in trends between the groups. Since I lack access to adequate pre-treatment data in order to provide evidence of parallel trends between treatment and control group, I investigate differences in changes between the groups between pre- and post-treatment data. The results provide an indication whether the significant differences in levels persist over time or if there are indications of changes in trends.

The results indicate that the gap between the groups decreases over time for a number of individual characteristics, such as access to water and sanitation, as well as labor market participation; suggesting that households in Ubudehe category 2 improved their

[8] Given that the vast majority of households payed an individual premium of RwF1000 prior to the policy change, the change in premium costs for individuals in Ubudehe category 3 represents a price increase of 200%.

welfare status relative to the households who were initially better off. However, there is no significant difference in the difference-in-difference estimates related to health measures and to consumption levels. The results suggest that the significant differences between the Ubudehe groups in relation to these characteristics is persistent over time. Significant differences in the difference-in-difference estimates suggest that the significant differences in baseline characteristics might change over time. This raises concerns regarding the presence of unobservable time-varying factors.

Table 4: Summary statistics

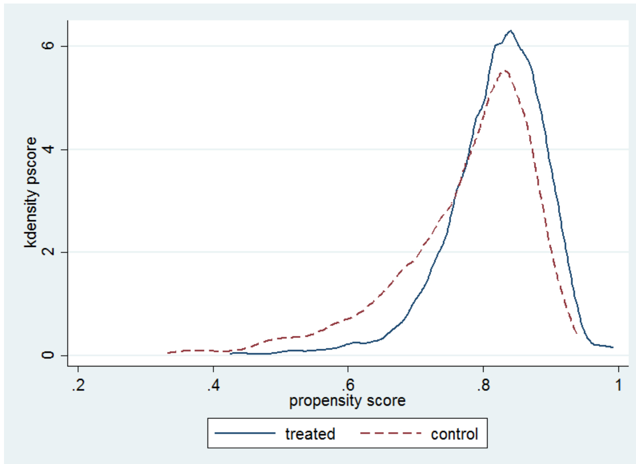
	Baseline				**Changes (2010-2014)**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	All	Ubudehe 2	Ubudehe 3	Diff	Ubudehe 2	Ubudehe 3	Diff-in-diff
Health issue	0.179	0.204	0.167	0.037***	0.069	0.062	-0.007
Disability	0.048	.070	.038	0.032***	.006	-.003	-.009
Piped water	0.329	.260	.325	-.064***	.166	.128	0.037**
Toilet	0.755	.665	.774	-.109***	.049	.099	.050***
Work	0.473	.464	.478	-.014	.100	.063	-.037***
Salary worker	0.238	.276	.235	.040***	.048	.018	-.030**
Poor	0.473	.634	.440	0.194***	-.082	-.079	0.003
Consumption HH	214 289.9	157 346.7	220 407	-63 060.28***	10 447.87	14 839.41	4 391.539
Rural	0.854	0.891	0.854	0.036***			
Age	22.663	23.958	22.077	0 1.882***	-	-	-
Female	0.529	.559	.518	0.041**			-
HH size	5.131	4.750	5.218	-0.467***	-	-	-
Travel time clinic	0.807	.886	.789	0.097***	-.117	-.014	.103*
Travel time hospital	3.109	3.443	3.030	0.414***	.105	.100	-0.005
Ubudehe 1	0.014						
Ubudehe 2	0.241						
Ubudehe 3	0.643						
Ubudehe 4	0.098						
Ubudehe 5	0.003						
Ubudehe 6	0.001						
Observations	5 484	1 321	3 524				

Note: *** p<0.01, ** p<0.05, * p<0.1.

Regarding the factors affecting the probability of being categorized in Ubudehe category 3, Table A7 reports the estimates from the logistic regression where the binary outcome variable takes the number 1 if the individual belongs to Ubudehe group 3, and 0 otherwise (Ubudehe group 2). The estimates in Table A7, column 1, are used to predict the likelihood of being classified as Ubudehe category 3, that is, of having received an increased premium cost after the policy change. In line with the descriptive statistics, the results suggest that there are a number of significant explanatory variables that predict the individual classification into Ubudehe groups. Relatively old and very young individuals (those over 65 years old and younger than 5 years old), as well as salary workers and individuals with a relatively low health status, were less likely to be categorized in Ubudehe category 3. Furthermore, an increase in household consumption and access to sanitation services is positively associated with the likelihood of being categorized in the higher Ubudehe category. However, the results shows that once we control for observable characteristics that explain the categorization of households into Ubudehe groups, the difference in health status disappear.

I assess the comparability of households in Ubudehe group 2 and 3 by looking at the distribution of covariates across household in the treatment and control group. Figure 5 illustrates the distribution of the predicted likelihood of being treated (categorized as Ubudehe 3) among individuals in Ubudehe group 2 and 3. The distribution shows a significant overlap between the treatment and control group, resulting in a wide region of common support. The distributions only lack common support at the low extreme of the propensity score distribution, showing that some of the individuals in the control group are substantially different from individuals in the treatment group and consequently run a significantly lower likelihood of being categorized in Ubudehe category 3. Figure 5 suggests that there is need for further adjustment of the sample in order to obtain a control group with similar characteristics as the treatment group. In a following section on sensitivity analysis (6.3) I restrict the sample based on individuals likelihood of being treated to provide estimations of the price elasticity of demand for CBHI based on relatively more balanced samples. Figure A1 shows that the overlap of the distribution in the predicted likelihood of being treated has improved as a result of this sample restriction.

Figure 5: Predicted likelihood of treatment - by treatment status, unmatched sample



6 Results

Table 5 presents estimations of the price sensitivity of demand for health insurance. These are estimates from a linear probability model (LPM) with individual fixed effect. The analysis indicates a negative correlation between price and the likelihood of being enrolled in the insurance. The results are robust to the inclusion of a number of covariates: the first column presents rough estimates of the price effect, only controlling for individual age and sex and distance to nearest hospital, the second column additionally controls for health status, including an indicator for whether an individual has a disability or was sick during the last two weeks prior to the interview, as well as indicators for whether the household count on access to piped water and sanitation. [9]

The preferred specification in column 3 implies that a RwF 1000 increase in the premium level is associated with a 9.16 percentage points decrease in the likelihood of being enrolled in the CBHI. This is equivalent to a 13.2% decrease at the mean (0.693). Across the entire sample, the policy change resulted in an increase in premium levels by 85.8% on average. From these estimations we can infer a price elasticity of the demand for health insurance of -0.17. Taken together the results indicate that although health insurance coverage is sensitive to price change, the overall demand is price inelastic.

[9] I also provide estimates including an indicator that takes the value of one if an individual receives the full premium subsidy. The subsidy dummy controls for this non-linearity where the price is close to zero.

Table 5: Price effect on the demand of health insurance

INSURANCE	(1)	(2)	(3)
Premium (RwF1000)	-0.0906***	-0.0912***	-0.0916***
	(0.0137)	(0.0136)	(0.0136)
Constant	0.865***	0.859***	0.829***
	(0.0564)	(0.0618)	(0.0610)
Observations	10,816	10,816	10,816
R-squared	0.042	0.045	0.048
Number of PID	5,488	5,488	5,488
Health covariates	No	Yes	Yes
Wealth control	No	No	Yes
Individual FE	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1. All regressions control for individual age, household consumption, distance to nearest health clinic. Furthermore, the specification includes indicators that equal 1 if individuals live in a rural ares, are working, are working as a salaried worker, were sick during the last 2 weeks, suffer from a disability, pr have access to piped water in community/household, count with a toilet or latrine with slab. Standard errors are clustered at household level.

6.1 Heterogeneity in Health Insurance Enrollment

This section investigates heterogeneity in the price sensitivity of demand for health insurance for individuals in a number of sub-samples. Table 6 presents the price sensitivity separated by age, gender, relation to household head and health risk. Overall, the estimates are similar between groups, the only exception being for spouses whose demand is less sensitive to price change. An increase in the premium level of RwF 1000 is associated with a 7.16 ppt decrease in the enrollment among spouses, compared to 9.83 ppt among household heads, witch corresponds to 10% and 14% respectively at mean. The results suggest that the effect of changes to premium costs is homogeneous among older and younger individuals, as well as among individuals with high and low health risk. Individual health status is based on a measure of the predicted likelihood of having been sick during the last two weeks.[10]

Table 7 shows heterogeneity in price sensitivity between individuals living in households with different socioeconomic status and demographic composition. The results indicate that price sensitivity varies with socioeconomic status. An increase in premium levels by RwF 1000 among individuals living in female headed households is associated with a decrease in the likelihood of being enrolled in the insurance by 13 ppt, compared to a 8 ppt decrease among male-headed households. This corresponds to a decrease of -0.20 and -0.11 respectively in the likelihood of being enrolled in the insurance. Similar differences are found between poor and non-poor households. An increase in premium prices of RwF1000 is associated with a decrease in enrollment by 23% at the mean among poor households, and 7% among non-poor households. The results are in line with previous empirical research suggesting that the price elasticity of demand for preventative healthcare varies with socioeconomic status, and is higher among less wealthy and vulnerable households (Dupas 2012). The estimated price sensitivity does not differ significantly between rural and urban households.

[10]Individual characteristics such as age, sex, income, disability, access to water and sanitation are explanatory variables used to predict the likelihood of having been sick

Table 6: Variation price effect

VARIABLES	(1) all	(2) head	(3) spouse	(4) child < 5 yrs	(5) senior > 50 yrs	(6) female	(7) male	(8) high risk	(9) low risk
Premium (RwF1000)	-0.0916***	-0.0983***	-0.0716***	-0.0906***	-0.0950***	-0.0907***	-0.0921***	-0.0979***	-0.0914***
Constant	0.829***	0.784***	0.808***	0.693***	0.954***	0.864***	0.783***	0.849***	0.826***
	(0.0610)	(0.150)	(0.189)	(0.0886)	(0.143)	(0.0684)	(0.0753)	(0.134)	(0.0636)
Observations	10,816	2,595	1,680	1,576	1,276	5,725	5,091	2,404	8,412
R-squared	0.048	0.055	0.025	0.051	0.084	0.049	0.048	0.065	0.056
Number of PID	5,488	1,375	879	1,072	707	2,901	2,587	1,324	4,369
Mean	0.693	0.708	0.733	0.676	0.722	0.699	0.689	0.708	0.689
Semi-elasticity	-0.132	-0.138	-0.098	-0.135	-0.132	-0.132	-0.132	-0.138	-0.132
Elasticity	-0.153	-0.170	-0.109	-0.128	-0.177	-0.155	-0.151	-0.174	-0.15

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions control for individual age, household consumption, distance to nearest health clinic, an indicator that equals one if the individual live in a rural area, is working, is working as a salary worker. Additionally, column 2 includes indicators that equals one if the individual was sick during the last 2 weeks, suffers from a disability, lives in a household that has access to piped water in community/household, lives in a household that counts with a toilet or latrine with slab. Column 3 further controls for household total consumption level. Clustered standard errors at household level.

Table 7: Variation price effect - between household

VARIABLES	(1) poor	(2) non-poor	(3) rural	(4) urban	(5) female head	(6) male head
Premium (RwF 1000)	-0.141***	-0.0548***	-0.0983***	-0.104**	-0.131***	-0.0754***
	(0.0290)	(0.0191)	(0.0153)	(0.0409)	(0.0209)	(0.0183)
Constant	0.749***	0.795***	0.756***	0.731***	0.737***	0.816***
	(0.188)	(0.0861)	(0.0500)	(0.166)	(0.126)	(0.0721)
Observations	4,749	6,067	9,319	1,497	2,332	8,484
R-squared	0.103	0.031	0.056	0.112	0.155	0.028
Number of PID	3,220	3,896	5,038	1,086	1,263	4,385
Mean	0.594	0.771	0.685	0.744	0.669	0.700
Semi-elasticity	-0.236	-0.071	-0.140	-0.143	-0.196	-0.107
Elasticity	-0.269	-0.086	-0.169	-0.144	-0.305	-0.118

Note: *** p<0.01, ** p<0.05, * p<0.1. All regressions control for individual age, household consumption, distance to nearest health clinic, indicator that equal 1 if individuals: live in a rural ares, is working, is working as a salary worker, was sick during the last 2 weeks, suffers from a disability, have access to piped water in community/household, count with a toilet or latrine with slab . Clustered standard errors at household level.

6.2 Sensitivity Analysis

Significant differences in observable characteristics between the treatment and control groups contribute to making the empirical analysis dependent on the modeling choice and specifications. By reducing the significant differences in explanatory variables between treatment and control groups, the treatment variable is closer to being independent of the background covariates which reduce the potential for bias (Ho et al. 2007). I do this by using non-parametric matching that makes the treatment group more similar to the control group. Cump et al. (2006) suggest a systematic approach that pre-screens the sample based on the predicted likelihood of being treated. The authors suggest that only individuals with a predicted likelihood of treatment between 0.1 and 0.9, that is, the sample is limited to only include observations within the common support and with a predicted likelihood of treatment of at least 10 percent, but no more than 90 percent. This matching ensures that there is overlap in the covariate distribution for all observations in the sample, i.e. the estimations require no extrapolation to cells without common support (Angrist and Pischke 2008), which, subsequently, contributes to less dependence on functional form. By matching the sample on the likelihood of being enrolled I ensure that there will always be a few observations in the control group that can be used to estimate the counterfactual.

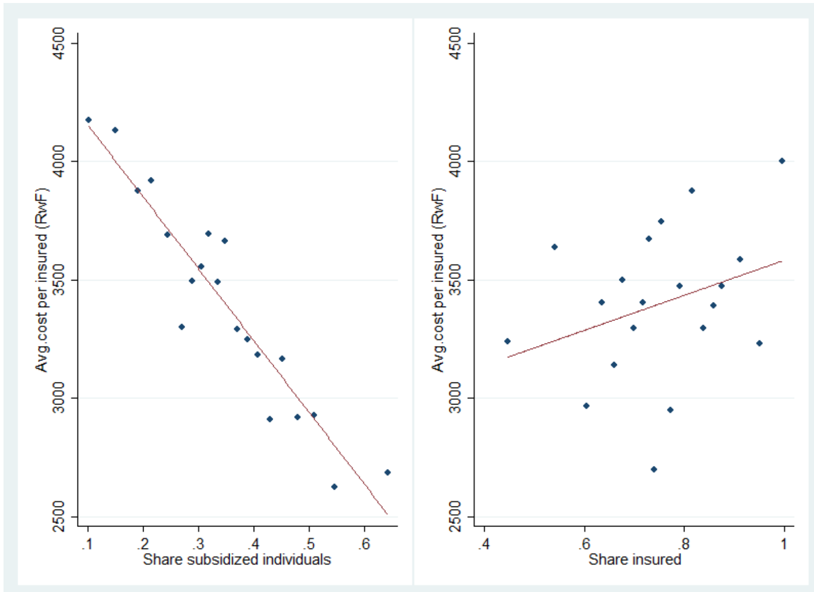
The results of the estimations using the matched sample are presented in Table A11. The estimates in the first column are based on a sample including all individuals in Ubudehe categories 2 and 3, excluding the households who received full subsidies prior to the policy change. Consequently, the analysis explores the variation in premium costs between two groups: households in Ubudehe group 2 whose premium costs changed from RwF 1000 to RwF 0 as a result of the policy change, and households in Ubudehe group 3 who saw a price increase from RwF 1000 to RwF 3000. This analysis provides estimates using a difference-in-difference approach with two treatment groups with different treatment intensity. The second column restricts this sample to only include individuals with a predicted likelihood of being treated within the common support, whereas the third column restricts the sample even further, in line with Crump et al. (2006), by including those with a propensity score within the common support between 0.1 and 0.9. The results indicate that the estimated price sensitivity is stable between the different samples. Furthermore, the estimates are similar to the price sensitivity estimated using the full sample. The results indicate that the main estimates of price sensitivity are not likely to suffer greatly from bias caused by different distributions in covariates between the different premium categories.

6.3 Insurer Costs and Selection

In this section I test for selection. Although some tests suggest that changes in premium levels are associated with changes in insurer costs, an indication of adverse selection, the results overall suggest that the adverse selection mechanism is not very strong.

The first graph in Figure 6 illustrates how average insurer cost among enrolled individuals covaries with the share of completely subsidized individuals in 2014. The results indicate that there is a negative association between the share of completely subsidized individuals in each health sector and average insurer costs. This suggests that there is a positive correlation between average price levels in each sector and the composition of the insured population, providing indicative evidence of adverse selection. The second graph shows the relation between average insurer costs per enrolled individual in each health sector, and the share of enrolled individuals in each sector. In contrast to the first graph, there is a positive association between the share of the population enrolled and the average insurer cost. In the presence of adverse selection, a larger share of enrollment is predicted to be associated with lower average insurer costs since the increase in enrollment leaves less room for selection.

Figure 6: Insurer costs and enrollment



The figures show the average insurance cost generated by enrolled individuals in each health sector in 2014. The first figure presents the correlation between average insurer costs and individuals in premium category 1 as a share of the total number of members in each sector. The second figure shows the correlation between the average insurer costs and the share of the total population enrolled in CBHI in each sector (the share of total population not enrolled in any other insurance scheme). The average cost is calculated as an average of the total costs for medical consultations, hospitalizations, reimbursement for services at health clinic and district hospitals , as well as administrative costs. The costs are calculated per sector. In each figure, the dots represent the average insurer cost per enrolled individual for a 5% enrollment bin.

Table A13 estimates the association between insurer costs and the share of subsidized and enrolled individuals in each health sector using a linear regression model, OLS. The estimations are based on cost data from the post-policy period, that is, after the introduction of the price change, and control for a number of sector characteristics that potentially could explain variation in insurer costs. I control for the age composition of each sector and other health related factors, such as access to protected sources of drinking water and sanitation. Furthermore, the cost estimations adjust for average consumption and share of the population living in urban areas, as well as district fixed effects. All health sectors pool resources in a district risk pool to cover the costs of district hospitals, etc. Consequently, it is likely that the financial set-up could influence the cost structures in each district. I control for such differences by the district fixed effects. The identification of the price sensitivity of insurer costs is based on variation in premium costs in the cross-section. As a result,the estimations rely solely on variation in costs between sectors with different average pricing.

In order to obtain an estimate of the cost curve, i.e. the direct relation between premium price and the average insurer costs, I calculate an average premium level for each sector. The average premium level is constructed as a weighted average of premium costs among the enrolled individuals and will consequently depend on the distribution of the enrolled individuals between the different premium categories in each health sector. In Table 8, column 3 shows the estimates of the average cost curve in equation 6. The last column presents the estimated association between average insurer costs and the average premium level in each sector. The results suggest that an increase in premium costs has a positive impact on average insurer costs. An increase of RwF 1000 in the average premium level is associated with an increase in average insurer costs by RwF 666. The slope of the cost curve represents a test for the existence and nature of selection in the market. A positive correlation indicates that individuals adversely select into the insurance scheme, that is, average cost increase among policyholders as the premium increases.

Table 8: Average insurer costs

	(1)	(2)	(3)
AVERAGE INSURER COSTS			
Share full subsidy	-2.132***		
	(0.357)		
Share enrolled		0.341	
		(0.385)	
Avg. premium (RwF1000)			0.666***
			(0.150)
Share access piped water	0.138	0.0948	0.145
	(0.155)	(0.169)	(0.158)
Share access sanitation	0.604*	0.627	0.613*
	(0.356)	(0.390)	(0.354)
Share urbanization	-0.0526	-0.0201	-0.0144
	(0.230)	(0.247)	(0.235)
Tot. population sector	6.04e-06	8.91e-06	6.19e-06
	(4.63e-06)	(5.44e-06)	(4.67e-06)
Share elderly	1.161	1.488	1.666
	(1.102)	(1.183)	(1.149)
Share childern < 5 yrs	0.583	0.910	1.080
	(1.044)	(1.104)	(1.063)
Avg. HH consumption	2.43e-07	2.52e-07	2.10e-07
	(3.95e-07)	(3.69e-07)	(3.91e-07)
Constant	3.212***	2.165***	1.027*
	(0.426)	(0.587)	(0.565)
Observations	318	318	318
R-squared	0.681	0.632	0.677

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

Table A13 in appendix presents estimations of the relation between average insurer cost and the share of individuals enrolled and completely subsidized. This Table includes different sector characteristic categories, where the last and preferred specification (column 4 and 8) include district fixed effects in order to control for systematic differences that could potentially correlate with administrative set-ups between the districts. Table A14 provides sensitivity estimations related to the effect of average premium costs on average insurer costs, controlling for different sets of covariates.

7 Simulations

Price sensitivity estimates can be used to evaluate a broader set of relevant policy counterfactuals. Table 9 shows the overall predicted take-up level for different premium structures. These calculations are based on the average price sensi tivity presented in table 5, column 3. The first row shows the predicted insurance coverage in 2014 considering the current premium structure. The simulations predict a take-up level of 0.714, which is consistent with the actual coverage rate of 0.712. The succeeding rows present the average enrollment levels for different subsidy structures. The results indicate that the overall enrollment rate would reach approximately 0.82 if all premiums were completely subsidized. This is consistent with previous literature that confirms full premium subsidies are not enough to induce universal health care (Finkelstein et al. 2017). A uniform premium cost of RwF 3000 results in a predicted coverage rate of 0.68, which is similar to the pricing at average insurer costs - RwF 3398, i.e a premium scheme without subsidies. The final rows predict take-up levels of targeted subsidies offering full premium subsidies to poor households (based on household consumption level), with children under 19 and 5 years respectively. In all three targeted subsidy strategies, households who are not subsidized face an individual premium of RwF 3000. Overall, the simulations suggest that changes to the premium subsidy scheme do not have a large impact on coverage levels. At the same time, all the subsidy strategies generate a higher insurance coverage compared to the unsubsidized premium structure based on average insurer cost.

The second portion of the table focuses on the implications of changes in premium costs related to average insurer cost and financial coverage level. Financial coverage is calculated as the share of the total costs that are covered by the premium income. Due to its definition, this measure of financial sustainability directly hinges upon the premium income and the average individual insurer cost predicted by each subsidy scheme. The results are presented in two scenarios, one that assumes no adverse selection and uses the average individual cost independent of the premium level;[11] and a second scenario that simulates the predicted average individual insurer cost using estimates of the cost function expressed by equation 6. The estimates are presented in table 8, column 3. I use this estimate price sensitivity to predict the relation between average premium costs and average insurer costs at the health sector level. The positive

[11] The average cost is calculated as a raw average of the administrative cost data provided by the Rwandan Government

slope of the average cost curve is reflected in the individual average cost levels related to each premium schemes: as the average premium cost increase, the average insurer cost increase. In relation to the uniform premium strategies, an increase in household premium costs is associated with an improved financial coverage level.

The simulations indicate that the financial sustainability of alternative premium subsidies differs depending on whether there is adverse selection or not. With adverse selection, the financial coverage reaches levels between 0.4 - 0.7 for the majority of subsidy schemes, meaning, household premiums cover approximately 40-70% of the insurer costs. However, in the absence of selection the range of coverage levels for the corresponding subsidy schemes are wider, suggesting that the coverage levels range between 0.3 - 0.9. Not surprisingly, the wedge between the level of financial coverage in the selection and no-selection scenarios increases as the premium levels deviate from the mean cost. The coverage levels for targeted premium schemes show similar levels of financial coverage. This is in contrast to the findings of previous studies on adverse selection (Parmar et al. 2012), where the results indicate that targeted subsidy schemes are associated with increased adverse selection. The results suggest that the effects of adverse selection are limited, but may be important from the insurers' point of view. The results are in line with previous results from developed countries that indicate that the cost of adverse selection (mainly in terms of social welfare) might be relatively negligible (Finkelstein et al. 2017; Sacks 2017).

Table 9: Financial sustainability and insurance coverage - alternative subsidy schemes

			No selection		**Selection**	
Premium structure	Predicted coverage	Premium payments	Avg.cost	Financial Coverage	Avg.cost	Financial Coverage
Actual premium (RwF 2255)	0.714	1.42e10	3526	0.62	3594	0.61
0	0.816	0.00	3526	0.00	2208	0.00
1000	0.771	7.03e09	3526	0.28	2882	0.35
2000	0.764	1.39e10	3526	0.57	3556	0.56
3000	0.679	1.86e10	3526	0.85	4230	0.71
3526 (Avg. cost)	0.661	2.05e10	3526	1.00	4593	0.77
Children (0-5 yrs free)	0.692	1.63e10	3526	0.73	3902	0.64
Minors (<19 yrs free)	0.744	9.23e09	3398	0.39	3166	0.43
Poor households free	0.735	1.23e10	3526	0.52	3963	0.46

Table 10 presents the effect of alternative premium subsidies on take-up within a number of subgroups. Based on the estimated variation in in price sensitivity between households with different socioeconomic status, it is expected that the predicted take-up of insurance for alternative premium subsidy scheme will vary between different socioeconomic groups. A premium scheme that targets poor households predicts higher insurance rates among individuals in this group in comparison with the current premium scheme that that targets households with low socioeconomic status. My simulations predict that the overall take-up level related to the actual premium subsidy achieves a coverage level of 71.4%, whereas take-up among individuals living in poor households only reaches 62%. This enrollment rate among the poor is relatively high compared to coverage in scenario with an actuarial premium that reflects the average expected insurer cost curve, but low compared to a scenario with a subsidy that targets the poor. Additionally, insurance coverage among children 5 years and younger is lower than average in the actual premium structure. The results indicate that a premium subsidy based on the monetary income could increase overall coverage levels, and more importantly increase access to health insurance among the poor. However, the simulations indicate that the coverage level among children will decrease.

Young children represent another potential group of interest for policymakers. The simulations indicate that targeted subsidies based on age will bring take-up levels over 80% among children 5 years and younger. It is important to note that take-up levels among poor individuals are low in relation to the age-based subsidy schemes. A premium structure that targets children 5 years and younger is predicted to contribute to low take-up levels of 58% among individuals living in financially poor households. On the other hand, enrollment rates among the youngest remain relatively high when subsidies target the financially poor.

There is not much difference in take-up levels between individuals with a predicted high health risk, compare to those with low risk. The predicted coverage levels indicate that individuals with high predicted health risk are more likely to enroll compared to those with low risk, for all subsidy schemes. Differences in coverage levels between high and low risk individuals does not vary significantly between the different premium schemes. This is important knowledge when considering the governmental goal of universal healthcare coverage; and that this conclusion has implications for financial sustainability, as the Rwandan Governemnt are likely to aim at insuring households with high health risk in order to prevent them from suffering from excessive healthcare expenditures.

Table 10: Insurance coverage - heterogeneous price sensitivity

Premium structure	poor	non-poor	children age < 6 yrs	senior age > 50 yrs	high risk	low risk
Actual premium	0.620	0.777	0.702	0,725	0.716	0.713
0	0.711	0.825	0.829	0,803	0.803	0.802
1000	0.661	0.807	0.775	0.764	0.760	0.772
2000	0.611	0.788	0.721	0.724	0.717	0.727
3000	0.561	0.769	0.667	0.685	0.675	0.682
3398 (Avg.cost)	0.567	0.725	0.663	0.686	0.680	0.655
Children <6 yrs free)	0.576	0.774	0.829	0.685	0.675	0.698
Minors (<19 yrs free)	0.644	0.792	0.829	0.685	0.675	0.765
Poor households free	0.711	0.769	0.741	0.723	0.722	0.738

8 Concluding Remarks

Over the last two decades, many governments in developing countries have taken measures toward achieving universal healthcare. In the developing country context, this often translates into a fundamental question of how to provide health insurance for households in the informal sector. CBHI has been proposed by a number of countries as a financial strategy to achieve universal access to healthcare. This insurance scheme is based on voluntary premium contributions paid by the insurance members. Due to often low levels of insurance take-up, voluntary health insurance schemes often lack financial sustainability, and are therefore often dependent on substantial premium subsidies provided by a number of foreign governments in order to expand insurance coverage.

This study suggests that the demand for CBHI is price inelastic. I find that an increase in premium costs by RwF 1000 (USD 1) contributes to an overall decrease in the likelihood of being enrolled by 9.16 ppt (13.2% at the mean). This translates into a price sensitivity of -0.15. Although changes to the price of insurance show significant effects on take-up, the change in demand is small in relation to the price change. Furthermore, the effect of changes to premium costs is heterogeneous between different subgroups of households. Individuals living in poor households or households headed by women have a higher price sensitivity compared to individuals in non-poor or male headed households.

The estimated price sensitivity is used to simulate take-up level, insurer costs and financial sustainability in relation to alternative subsidy schemes. Overall, the results indicate that governmental subsidy strategies will have a limited effect on the insurance coverage. This is a direct effect of the inelastic demand. The results suggest that the current premium scheme achieves a relatively high coverage level compared to the other counterfactual subsidy strategies. However, when analyzing the predicted coverage by sub-groups, the evidence indicates that there is great variation. Although one of the primary aims of the new premium policy in Rwanda was to increase equity in the access to health care (Ministry of Health 2016), the results suggest that the current premium scheme does not achieve high enrollment levels among poor households compared to the alternative premium structures. According to the simulations, the implementation of a subsidy scheme that targets poor households would not only contribute to an increase in the overall insurance coverage but would also increase insurance take-up among individuals living in poor households as well as among the youngest children. Consequently, a premium scheme that targets monetary poor households is likely to increase equity in the access to healthcare. However, it is important to note that the CBHI scheme primarily targets households in the informal sector. In this context, classification of households according to income could be problematic, implying that the implementation of this premium subsidy policy might not be feasible from a practical point of view.

Another aim of the Rwandan policy reform was to increase financial sustainability of the insurance scheme by increasing revenue from household premium payments (Ministry of Health 2016). I simulate the financial coverage related to the different pricing strategies by calculating the share of insurer costs covered by premium revenue. In addition to the predicted coverage levels, I use variation in aggregate premium costs between administrative health sectors to identify the average cost curve of the insurer. The results show a strong correlation between premium costs and insurer costs, consistent with adverse selection. The presence of adverse selection is important for financial sustainability of the insurance scheme. As the premium costs increase, so do the cost of providing insurance for insurance beneficiaries. By predicting the financial coverage levels of subsidy schemes both in a setting that allows for adverse selection and one that assumes no selection, I provides suggestive evidence of the financial costs related to adverse selection. This is important knowledge that can inform policymakers as to how adverse selection translates into future costs faced by the insurer and, by extension, how to predict the financial coverage of different policy instruments related to pricing in the insurance market.

The results indicate that the financial effects of adverse selection is limited in relation to many subsidy schemes. At the same time, adverse selection is likely to contribute to unsustainable insurance schemes: as premium costs increase so does the cost of providing insurance coverage among beneficiaries. According to the simulations of insurance coverage, a premium cost that intends to cover average insurer costs will, due to adverse selection, result in increased insurer costs. As premium costs increase in order to cover average insurer costs, so do the cost of the remaining beneficiaries. Furthermore, in relation to the aim of reaching universal healthcare coverage, the take-up levels related to relatively high premium costs are far from universal. In the end, a health insurance scheme financed by household premiums is not likely to represent a financially sustainable strategy to reach universal health coverage.

The question of how to finance the expansion of health insurance is important for the long-run sustainability of these health insurance schemes, and my study is the first to provide suggestive evidence of the financial costs of adverse selection in the voluntary health insurance market in the developing country context. Household premiums are not likely to promote universal insurance coverage without the support of external funds. In the long run, governments should find other potential sources of funding that does not rely on the need of international external funding. However, due to the small tax base in countries with extended informal sectors the limitations of tax-based financing is obvious in the short run. Despite this, a number of countries have decided to put legal tax commitments towards financing the expansion of national social health insurance schemes. Premium subsidies can represent a good alternative to expand CBHI in the short run.

References

[1] Sarah Alkenbrack, Bart Jacobs, and Magnus Lindelow. Achieving universal health coverage through voluntary insurance: what can we learn from the experience of lao pdr? *BMC health services research*, 13(1):521, 2013.

[2] Joshua D Angrist and Jörn-Steffen Pischke. *Mostly harmless econometrics: An empiricist's companion*. Princeton university press, 2008.

[3] Abhijit Banerjee, Esther Duflo, and Richard Hornbeck. Bundling health insurance and microfinance in india: There cannot be adverse selection if there is no demand. *American Economic Review*, 104(5):291–97, 2014.

[4] Agnes Binagwaho, Renate Hartwig, Denyse Ingeri, and Andrew Makaka. Mutual health insurance and the contribution to improvements in child health in rwanda. *Erasmus University. Rotterdam, Netherlands: International Institute of Social Studies*, 2012.

[5] M Kate Bundorf, Jonathan Levin, and Neale Mahoney. Pricing and welfare in health plan choice. *American Economic Review*, 102(7):3214–48, 2012.

[6] Joseph J Capuno, Aleli D Kraft, Stella Quimbo, Carlos R Tan Jr, and Adam Wagstaff. Effects of price, information, and transactions cost interventions to raise voluntary enrollment in a social health insurance scheme: A randomized experiment in the philippines. *Health economics*, 25(6):650–662, 2016.

[7] Benjamin Chemouni. The political path to universal health coverage: Power, ideas and community-based health insurance in rwanda. *World Development*, 106:87–98, 2018.

[8] Pierre-André Chiappori and Bernard Salanie. Testing for asymmetric information in insurance markets. *Journal of political Economy*, 108(1):56–78, 2000.

[9] Jessica Cohen and Pascaline Dupas. Free distribution or cost-sharing? evidence from a randomized malaria prevention experiment. *The Quarterly Journal of Economics*, pages 1–45, 2010.

[10] Shawn Cole, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. Barriers to household risk management: Evidence from india. *American Economic Journal: Applied Economics*, 5(1):104–35, 2013.

[11] Richard Crump, V Joseph Hotz, Guido Imbens, and Oscar Mitnik. Moving the goalposts: Addressing limited overlap in the estimation of average treatment effects by changing the estimand, 2006.

[12] Pascaline Dupas. Health behavior in developing countries. *Annu. Rev. Econ.*, 3(1):425–449, 2011.

[13] Liran Einav, Amy Finkelstein, and Mark R Cullen. Estimating welfare in insurance markets using variation in prices. *The quarterly journal of economics*, 125(3):877–921, 2010.

[14] Liran Einav, Amy Finkelstein, and Jonathan Levin. Beyond testing: Empirical models of insurance markets. *Annu. Rev. Econ.*, 2(1):311–336, 2010.

[15] Daniel E Ho, Kosuke Imai, Gary King, and Elizabeth A Stuart. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis*, 15(3):199–236, 2007.

[16] Dean Karlan, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129(2):597–652, 2014.

[17] Berber Kramer. Intra-household allocations of micro health insurance: No adverse selection after all? 2015.

[18] Michael Kremer and Edward Miguel. The illusion of sustainability. *The Quarterly journal of economics*, 122(3):1007–1065, 2007.

[19] Judith Lammers, Susan Warmerdam, and Rotterdam Ecorys. Adverse selection in voluntary micro health insurance in nigeria. *AIDS Research Series*, 6, 2010.

[20] David Levine, Rachel Polimeni, and Ian Ramage. Insuring health or insuring wealth? an experimental evaluation of health insurance in rural cambodia. *Journal of Development Economics*, 119:1–15, 2016.

[21] Chunling Lu, Brian Chin, Jiwon Lee Lewandowski, Paulin Basinga, Lisa R Hirschhorn, Kenneth Hill, Megan Murray, and Agnes Binagwaho. Towards universal health coverage: an evaluation of rwanda mutuelles in its first eight years. *PLoS One*, 7(6):e39282, 2012.

[22] Ahmed Mushfiq Mobarak and Mark Rosenzweig. Risk, insurance and wages in general equilibrium. Technical report, National Bureau of Economic Research, 2014.

[23] Ha Nguyen and James Knowles. Demand for voluntary health insurance in developing countries: the case of vietnams school-age children and adolescent student health insurance program. *Social Science & Medicine*, 71(12):2074–2082, 2010.

[24] Ministry of Health Rwanda. The development of community-based health insurance in rwanda: Experiences and lessons. *Technical Brief*, 2016.

[25] Divya Parmar, Manuela De Allegri, Germain Savadogo, and Rainer Sauerborn. Do community-based health insurance schemes fulfil the promise of equity? a study from burkina faso. *Health Policy and Planning*, 29(1):76–84, 2014.

[26] Divya Parmar, Aurélia Souares, Manuela De Allegri, Germain Savadogo, and Rainer Sauerborn. Adverse selection in a community-based health insurance scheme in rural africa: implications for introducing targeted subsidies. *BMC health services research*, 12(1):181, 2012.

[27] DW Sacks. How do the mandate and the premium tax credit affect the individual insurance market. Technical report, Technical report, Working Paper, 2017.

[28] Rebecca L Thornton, Laurel E Hatt, Erica M Field, Mursaleena Islam, Freddy Solís Diaz, and Martha Azucena González. Social security health insurance for the informal sector in nicaragua: a randomized evaluation. *Health economics*, 19(S1):181–206, 2010.

[29] Adam Wagstaff, Ha Thi Hong Nguyen, Huyen Dao, and Sarah Bales. Encouraging health insurance for the informal sector: a cluster randomized experiment in vietnam. *Health economics*, 25(6):663–674, 2016.

[30] Hong Wang, Licheng Zhang, Winnie Yip, and William Hsiao. Adverse selection in a voluntary rural mutual health care health insurance scheme in china. *Social science & medicine*, 63(5):1236–1245, 2006.

[31] Licheng Zhang and Hong Wang. Dynamic process of adverse selection: evidence from a subsidized community-based health insurance in rural china. *Social science & medicine*, 67(7):1173–1182, 2008.

A Appendix

Table A1: Correlation between Ubudehe categories and consumption poverty, 2010

	(1)	(2)
VARIABLES	Non-poor	Poor
Ubudehe 1	37%	63%
Ubudehe 2	41%	59%
Ubudehe 3	60%	40%
Ubudehe 4	73%	27%
Ubudehe 5	91%	9%
Ubudehe 6	100%	0%
Observations	56%	43%

Table A2: Summary statistics by insurance status

VARIABLES	(1) All	(2) Insured	(3) Not insured	(4) Diff
Insurance	0.674	1	0	-
Health issue	0.179	0.180	0.176	-0.004
Disability	0.048	0.048	0.048	-0.001
Piped water	0.329	0.341	0.306	-0.035***
Sanitation	0.756	0.800	0.665	-0.135***
Work	0.473	0.490	0.438	-0.052***
Salary worker	0.238	0.223	0.270	0.047***
Poor	0.472	0.402	0.618	0.217***
Consumption HH (RwF1000)	227.687	253.357	174.522	-78835.07***
Rural	0.854	0.842	0.878	0.036***
Age	22.684	23.360	21.286	-2.074***
Female	0.529	0.532	0.522	-0.010***
HH size	5.130	5.084	5.224	0.140**
Travel time clinic (hours)	0.808	0.754	0.919	0.165***
Travel time hospital (hours)	3.108	3.064	3.201	0.138**
Ubudehe 1	0.014	0.010	0.022	0.012***
Ubudehe 2	0.241	0.204	0.317	0.112***
Ubudehe 3	0.642	0.672	0.580	-0.093***
Ubudehe 4	0.098	0.109	0.077	-0.032***
Ubudehe 5	0.003	0.004	0.001	-0.003*
Ubudehe 6	0.002	0.001	0.004	0.003**
Observations	5 481	3 694	1 787	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Summary statistics by premium category

VARIABLES	All	Category 1	Category 2	Category 3
Health issue	0.179	0.209	0.168	0.185
	(0.383)	(0.407)	(0.374)	(0.395)
Disability	0.048	0.075	0.038	0.037
	(0.214)	(0.263)	(0.193)	(0.192)
Piped water	0.329	0.255	0.350	1
	(0.469)	(0.436)	(0.477)	(0)
Sanitation	0.756	0.653	0.789	0.869
	(0.429)	(0.475)	(0.407)	(0.344)
Work	0.473	0.470	0.474	0.481
	(0.499)	(0.499)	(0.499)	(0.509)
Salary worker	0.238	0.281	0.223	0.148
	(0.425)	(0.450)	(0.416)	(0.362)
Poor	0.472	0.629	0.421	0
	(0.499)	(0.483)	(0.493)	(0)
Consumption HH (RwF1000)	214 289	157 617	231 798	566 158
	(213 351)	(114 456)	(233 063)	(305 416)
Rural	0.854	0.885	0.842	1
	(0.352)	(0.318)	(0.364)	(0)
Age	22.684	24.437	22.085	16.956
	(19.049)	(21.322)	(18.190)	(13.663)
Female	0.529	0.562	0.517	0.521
	(0.499)	(0.496)	(0.499)	(0.510)
HH size	5.130	4.705	5.271	6.217
	(2.125)	(1.888)	(2.184)	(1.346)
Travel time clinic (hours)	0.808	0.883	0.784	0.304
	(0.770)	(0.761)	(0.470)	(0.470)
Travel time hospital (hours)	3.108	3.401	3.014	2.217
	(1.980)	(2.032)	(1.950)	(2.087)
Observations	5 481	1 398	4 063	127

I use a number of different strategies to identify households who received full subsidy before the policy change. The estimates presented in the first column assumes that subsidized households belong to Ubudehe category 1 or 2 and are classified as extremely poor according to the national monetary poverty measure (consumption). Column 2, uses the same definition as poverty1 with the only exception that it also includes individuals from Ubudehe category 3, as long as they are classified as extremely poor according to the alternative measurement, whereas the last column defines all households in Ubudehe category 1 as fully subsidized before the policy change. This definition implies that approximately 2% of the sample received completely subsidized premiums prior to the policy change.

The three columns use the different definitions of the premium that were discussed earlier. The coefficients are stable to changes in the definition of the premium change. All specifications control for age, health and labor status.

Table A4: Price effect on the demand of health insurance, individual FE, different premium variations

	(1)	(2)	(3)
INSURANCE			
Premium (poverty 1)	-0.0916***		
	(0.0136)		
Premium (poverty 2)		-0.0837***	
		(0.0124)	
Premium (Ubudehe)			-0.0865***
			(0.0129)
Constant	0.829***	0.806***	0.835***
	(0.0610)	(0.0604)	(0.0608)
Observations	10,816	10,816	10,816
R-squared	0.048	0.048	0.050
Number of PID	5,488	5,488	5,488

Note: *** p<0.01, ** p<0.05, * p<0.1. All regressions control for individual age, household consumption, distance to nearest health clinic. Furthermore, the specification includes indicators that equal 1 if individuals live in a rural ares, are working, are working as a salaried worker, were sick during the last 2 weeks, suffer from a disability, pr have access to piped water in community/household, count with a toilet or latrine with slab . Standard errors are clustered at household level.

Table A5: Ubudehe classification

Group	Characteristics
Category 1 (those living in abject poverty)	This category of the population owns no property, lives by begging and is wholly dependent on others
Category 2 (very poor)	This category has poor housing, lives on a poor diet, depends on others and does not own land or livestock
Category 3 (poor)	This category is malnourished, owns a small portion of land, has low production capacity and cannot afford secondary education for their children
Category 4 (resourceful poor)	Own some land, cattle, a bicycle and have average production capacity. Their children can afford secondary school and have fewer difficulties accessing healthcare
Category 5 (food rich)	This group own large areas of land, can afford a balanced diet, and live in decent homes. They employ others, own cattle, and can afford university education for their child
Category 6 (money rich)	This category of the population have money in banks, can receive bank loans, own an above average house, a car, livestock, fertile lands, have access to sufficient food and have permanent employment

Table A6: Household Income and Premium Costs

Ubudehe	Mean consumption (RwF)		Mean premium (RwF)		Share of income (%)	
	2010	2014	2010	2014	2010	2014
Ubudehe 1	176 161	176 286	1278	0		0
Ubudehe 2	178 116	190 412	2613	0		0
Ubudehe 3	249 997	261 330	4272	12917	1.7	4.9
Ubudehe 4	366 723	389 565	4767	14479	1.2	3.9
Ubudehe 5	484 501	251 214	5333	45500	1.1	9.3
Ubudehe 6	9 673 526	4 848 838	4000	38500	-	-

Table A7: Likelihood of treatment

VARIABLES	(1) Ubudehe 2 & 3	(2) common support	(3) $0.1 - 0.9$
Health status	-0.143	-0.137	-0.142
	(0.102)	(0.103)	(0.104)
Disability	-0.426**	-0.389**	-0.404**
	(0.175)	(0.178)	(0.178)
Work	0.0892	0.0729	0.0573
	(0.160)	(0.161)	(0.166)
Salary worker	-0.282**	-0.273**	-0.290**
	(0.119)	(0.120)	(0.124)
Consumption (RwF 1000)	0.000477*	0.000493*	0.000516*
	(0.000260)	(0.000269)	(0.000304)
Rural	0.143	0.160	0.207*
	(0.120)	(0.120)	(0.122)
Age6_19	-0.325***	-0.328***	-0.359***
	(0.116)	(0.117)	(0.120)
Age20_29	0.250	0.237	0.208
	(0.195)	(0.196)	(0.203)
Age30_39	0.205	0.224	0.203
	(0.210)	(0.212)	(0.219)
Age40_49	0.0603	0.0514	0.0402
	(0.228)	(0.228)	(0.235)
Age50_65	-0.0860	-0.102	-0.0742
	(0.209)	(0.210)	(0.214)
Age65_more	-0.719***	-0.648***	-0.677***
	(0.229)	(0.233)	(0.235)
Female	-0.135*	-0.136*	-0.129
	(0.0810)	(0.0814)	(0.0832)
Household size	0.186***	0.183***	0.170***
	(0.0229)	(0.0235)	(0.0257)
Protected water source	0.315***	0.295***	0.271***
	(0.0949)	(0.0953)	(0.0982)
Sanitation	0.319***	0.273***	0.275***
	(0.0898)	(0.0911)	(0.0919)
Time arrive clinic (hours)	0.0249	0.00927	0.0145
	(0.0531)	(0.0534)	(0.0543)
Constant	0.226	0.285	0.318
	(0.220)	(0.224)	(0.233)
Observations	4,336	4,274	3,923

Figure A1: Predicted likelihood of treatment - by treatment status, matched sample

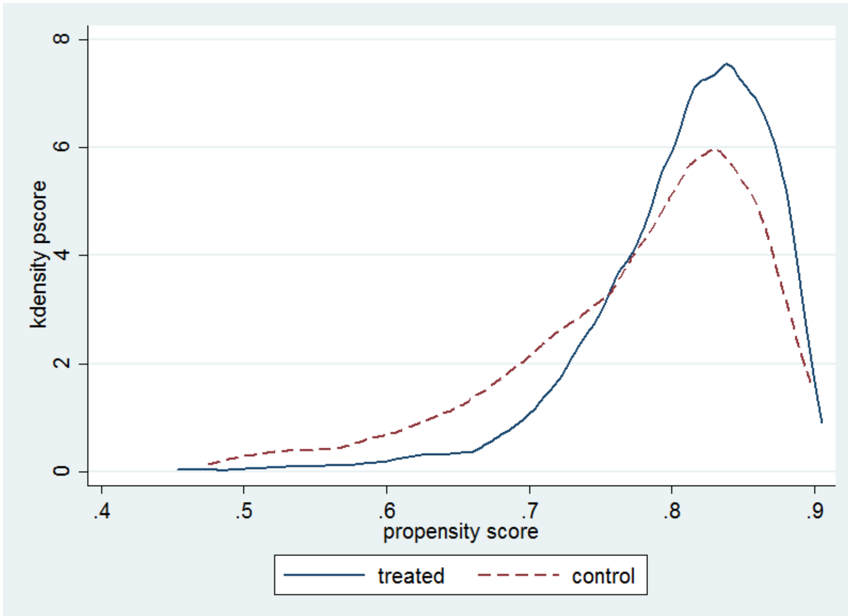


Table A8: Price sensitivity, controlling for non-linearity

	(1)	(2)	(3)
INSURANCE			
Premium (RwF1000)	-0.125***	-0.125***	-0.122***
	(0.0343)	(0.0340)	(0.0341)
Full subsidy	-0.136	-0.132	-0.121
(dummy=1 if premium=0)	(0.103)	(0.102)	(0.103)
Constant	0.913***	0.904***	0.873***
	(0.0675)	(0.0714)	(0.0712)
Observations	10,816	10,816	10,816
R-squared	0.044	0.047	0.049
Number of PID	5,488	5,488	5,488

*** p<0.01, ** p<0.05, * p<0.1. All regressions control for individual age, household consumption, distance to nearest health clinic. Furthermore, the specification includes indicators that equal 1 if individuals live in a rural ares, are working, are working as a salaried worker, were sick during the last 2 weeks, suffer from a disability, or have access to piped water in community/household, count with a toilet or latrine with slab. Standard errors are clustered at household level.

Table A9: Heterogeneity price sensitivity - household characteristics, controlling for non-linearity

VARIABLES	(1) all	(2) poor	(3) non-poor	(4) rural	(5) urban	(6) female hh head	(7) male hh head
Premium (RwF1000)	-0.122**	-0.193***	0.0995	-0.126***	-0.522***	-0.251***	-0.0500
	(0.0351)	(0.0431)	(0.0673)	(0.0363)	(0.0620)	(0.0415)	(0.0429)
Full subsidy	-0.121	-0.275*	0.526**	-0.111	-1.293***	-0.441***	0.103
(dummy=1 if premium=0)	(0.0937)	(0.148)	(0.209)	(0.108)	(0.185)	(0.126)	(0.135)
Constant	0.873***	0.904***	0.618***	0.796***	1.273***	0.961***	0.780***
	(0.0466)	(0.201)	(0.114)	(0.0630)	(0.197)	(0.130)	(0.0869)
Observations	10,816	4,749	6,067	9,319	1,497	2,332	8,484
R-squared	0.049	0.112	0.045	0.057	0.149	0.189	0.028
Number of PID	5,488	3,220	3,896	5,038	1,086	1,263	4,385

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions control for individual age, household consumption, distance to nearest health clinic, indicator that equal 1 if individuals: live in a rural ares, is working, is working as a salary worker, was sick during the last 2 weeks, suffers from a disability, have access to piped water in community/household, count with a toilet or latrine with slab . Clustered standard errors at household level.

Table A10: Heterogeneity price sensitivity - individual characteristics, controlling for non-linearity

VARIABLES	(1) head	(2) spouse	(3) child < 5 yrs	(4) senior > 65 yrs	(5) female	(6) male	(7) high risk	(8) low risk
Premium (RwF1000)	-0.117***	-0.0523	-0.108*	-0.187***	-0.128***	-0.115***	-0.137***	-0.121***
	(0.0320)	(0.0444)	(0.0624)	(0.0490)	(0.0326)	(0.0419)	(0.0350)	(0.0386)
Full subsidy	-0.0713	0.0766	-0.0673	-0.315**	-0.147	-0.0917	-0.139	-0.121
(dummy=1 if premium=0)	(0.0994)	(0.140)	(0.192)	(0.151)	(0.0988)	(0.127)	(0.107)	(0.116)
Constant	0.802***	0.772***	0.717***	1.059***	0.918***	0.816***	0.893***	0.871***
	(0.152)	(0.202)	(0.118)	(0.154)	(0.0772)	(0.0875)	(0.139)	(0.0769)
Observations	2,595	1,680	1,576	1,276	5,725	5,091	2,404	8,412
R-squared	0.056	0.026	0.052	0.095	0.052	0.049	0.067	0.057
Number of PID	1,375	879	1,072	707	2,901	2,587	1,324	4,369

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions control for individual age, household consumption, distance to nearest health clinic. Furthermore, the specification includes indicators that equal 1 if individuals live in a rural ares, are working, are working as a salaried worker, were sick during the last 2 weeks, suffer from a disability, pr have access to piped water in community/household, count with a toilet or latrine with slab . Standard errors are clustered at household level.

Table A11: Price sensitivity, matched samples

VARIABLES	(1) Ubudehe 2 & 3	(2) common support	(3) pscore 0.1 - 0.9
Premium (RwF 1000)	-0.0911***	-0.0925***	-0.0923***
	(0.0134)	(0.0135)	(0.0137)
Constant	0.823***	0.825***	0.812***
	(0.0676)	(0.0671)	(0.0697)
Observations	9,051	8,431	7,743
R-squared	0.045	0.046	0.044
Number of PID	4,833	4,274	3,923

Note: *** p<0.01, ** p<0.05, * p<0.1. All regressions control for individual age, household consumption, distance to nearest health clinic. Furthermore, the specification includes indicators that equal 1 if individuals live in a rural ares, are working, are working as a salaried worker, were sick during the last 2 weeks, suffer from a disability, pr have access to piped water in community/household, count with a toilet or latrine with slab . Standard errors are clustered at household level.

Table A12: Nature of reported health issues, 2010 and 2014

ILLNESS	(1) 2011 (%)	(2) 2014 (%)
Malaria	17.31	25.61
Internal parasites	24.13	22.57
Respiratory infection	26.58	21.35
Skin disease	5.50	4.26
Accident/Injury	5.80	4.71
Diarrhea	1.12	0.61
Dental problem	4.48	4.33
Reproductive issues	0.41	0.84
Other	14.66	15.73
Total	100	100

Table A13: Sector average cost per individual, avg. 2013-2014

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share full subsidy	-3.037***	-3.012***	-2.989***	-2.132***				
	(0.442)	(0.443)	(0.454)	(0.357)				
Share enrollment					0.742*	0.832*	0.772*	0.341
					(0.431)	(0.433)	(0.432)	(0.385)
Share access piped water		0.299	0.259	0.138		0.346*	0.314	0.0948
		(0.195)	(0.216)	(0.155)		(0.207)	(0.232)	(0.169)
Share access sanitation		0.0216	-0.0201	0.604*		0.360	0.384	0.627
		(0.300)	(0.321)	(0.356)		(0.334)	(0.365)	(0.390)
Level urbanization				-0.0526				-0.0201
				(0.230)				(0.247)
Total population (sector)			2.46e-07	6.04e-06			7.69e-06	8.91e-06
			(5.55e-06)	(4.63e-06)			(6.10e-06)	(5.44e-06)
Share elderly			-0.692	1.161			-0.363	1.488
			(1.779)	(1.102)			(1.915)	(1.183)
Share youn children < 5 yrs			1.046	0.583			1.858	0.910
			(1.281)	(1.044)			(1.359)	(1.104)
Avg. HH consumption			6.93e-08	2.43e-07			-2.87e-07	2.52e-07
			(5.60e-07)	(3.95e-07)			(6.66e-07)	(3.69e-07)
Constant	4.459***	4.289***	4.224***	3.212***	2.841***	2.306***	1.987***	2.165***
	(0.147)	(0.293)	(0.547)	(0.426)	(0.329)	(0.483)	(0.691)	(0.587)
District FE	No	No	No	Yes	No	No	No	Yes
Observations	318	318	318	318	318	318	318	318
R-squared	0.155	0.162	0.165	0.681	0.009	0.023	0.036	0.632

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

Table A14: Premium and average cost, avg. 2013-2014

VARIABLES	(1)	(2)	(3)	(4)
Avg. premium (RwF1000)	0.990***	0.993***	0.979***	0.666***
	(0.142)	(0.143)	(0.150)	(0.150)
Share access piped water		0.376**	0.364*	0.145
		(0.191)	(0.214)	(0.158)
Share access sanitation		0.0353	0.0393	0.613*
		(0.291)	(0.315)	(0.354)
Level urbanization			-0.221	-0.0144
			(0.248)	(0.235)
Share elderly			-0.782	1.666
			(1.728)	(1.149)
Share young children < 5 yrs			1.231	1.080
			(1.315)	(1.063)
Total population (sector)			-2.66e-06	6.19e-06
			(5.64e-06)	(4.67e-06)
Avg. HH consumption			4.32e-07	2.10e-07
			(5.30e-07)	(3.91e-07)
Constant	1.477***	1.260***	1.175**	1.027*
	(0.286)	(0.376)	(0.550)	(0.565)
District FE	No	No	No	Yes
Observations	318	318	318	318
R-squared	0.176	0.187	0.194	0.677

Robust standard errors in parentheses

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