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Abstract

We investigate the properties of health insurance demand in Burkina Faso, where we offered poor households a voluntary health insurance product at half the usual price. The targeting procedure we implemented delivers a fuzzy regression discontinuity design, which identifies the price elasticity of demand for health insurance as well as associated selection effects. We find large price elasticities among urban households, whereas the demand of rural households is price-inelastic. There are important selection effects, with widowed male household heads being most price-sensitive. Correlating these heterogeneous effects with survey data on informal transfers and health expenditures, our results suggest that informal risk-sharing largely crowds out formal insurance and that a single insurance product may fail to align with poor households' small health budgets. We find no adverse selection into health insurance.

Keywords: *Health insurance; Micro-health insurance; Social health insurance; Health insurance demand; Targeting; Adverse selection*

JEL Codes: G22, I13, I38, O15

1 Introduction

Illness is one of the most frequent economic shocks to households in low and middle-income countries (World Bank, 2014). Apart from an immediate deprivation in well-being, health shocks cause indirect costs by preventing individuals from engaging in income-earning activities and triggering high out-of-pocket expenditures for medical care at the same time. Therefore, health shocks constitute a severe, unpredictable economic risk that threatens households' short- and long-term consumption (Wagstaff, 2007). Relative to informal arrangements, formal insurance schemes have the potential to offer better financial protection by providing more efficient risk pooling and by avoiding the enforcement and commitment problems of informal risk-sharing networks (Ligon et al., 2002). Through less healthy working and living conditions, the poor are especially exposed to the risk of ill health while having little access to formal insurance (Gertler and Gruber, 2002). One popular way to provide access to health insurance in low and middle-income countries has been voluntary social health insurance. This model is similar to private health insurance but typically features subsidization by the state and simpler procedures, typically with a uniform premium independent of an insuree's observable characteristics. As for other forms of microinsurance, such as index-based crop insurance for farmers, take-up rates consistently fall short of policy targets (Eling et al., 2014).

In this paper we study the demand for voluntary health insurance in the context of a pilot health insurance program introduced in one administrative department of Burkina Faso. While all households were offered individual-level health insurance policies, a 50 percent subsidy on the individual premium was offered to the poorest quintile of households in each village and urban neighborhood. A household's poverty status was determined through community wealth rankings. Combined with administrative data from the insurance provider, we develop an original fuzzy regression discontinuity design implied by the community targeting mechanism, which elicits insurance demand elasticities for households at the poverty threshold. The richness of our data, which includes a demographic and an economic census, allows us to identify heterogeneous effects of pricing across subpopulations and to distinguish between household-level and individual-level enrollment. Moreover, by correlating the heterogeneous treatment effects with economic and demographic characteristics across population subgroups, we identify some key predictors of demand levels and elasticities in a poor economy. Finally, with data on insurance claims and health facility utilization, we test for adverse selection into health insurance by assessing whether insurees' unobserved risk, which we measure by the value of insurance benefits, correlates with the exogenously varied insurance price.

Our findings are as follows. Subsidization has moderate absolute but large relative effects on enrollment, with important differences between rural and urban sectors. Urban households around the eligibility threshold, which are moderately poor by international standards, more than triple enrollment, from initially 10 to 35 percent, when offered a 50 percent discount, and individual enrollment increases from 6 to 23 percent. For the urban areas, the targeted vouchers of our intervention increase equity in access to health insurance along the wealth distribution as enrollment among the poorest quintile of urban households ties with enrollment in the wealthiest quartile. In contrast, subsidization is ineffective for rural households at the eligibility threshold, which are ultra-poor by international standards. Regarding selection into insurance, we find that subsidization attracts almost exclusively households headed by a widowed male. There are no gender disparities caused by subsidization, but individuals who get additionally enrolled are primarily elderly. Coverage among individuals aged above 55 increases drastically, from seven to fifty percent, while the increase is only fifteen percent for prime-aged adults and close to zero for children. This pattern is driven by the heterogeneous extensive margin effects as widower-headed households have fewer children and more elderly in our study context.

In contrast to these important effects by household head characteristics, we find only small and statistically insignificant negative differences in health care facility utilization and implied indemnification payments between unsubsidized and subsidized insured individuals. This finding holds conditional on observable characteristics of insurees as well as unconditionally. While the signs of our point estimates are opposite to classical adverse selection, that is a lower premium attracts somewhat greater risks, the magnitude of these differences is small and statistically far from significant.

While our research design contains no experimental variation in dimensions other than insurance pricing, we attempt to identify the causes of the lack of demand as well as the channels driving heterogeneity in demand elasticities across different types of households. An important driver of the lack of demand that our data suggest is a mismatch between the price of the health insurance policy on the one hand and poor households' desired health budgets on the other. According to household survey data collected prior to our subsidization campaign, urban households around the voucher eligibility threshold have medical expenses equal to only about one half the regular insurance premium, while this figure equals only one quarter for rural households. As a consequence, the subsidized insurance premium roughly matches poor urban households' desired medical expenses while rural households' revealed preference for medical budgets falls far short of even the subsidized premium. Second, the survey data suggest that informal risk sharing between households is intense. Informal receipts from friends and relatives are a multiple of households' health expenditures in rural and urban sectors alike. Given that health shocks are largely idiosyncratic, actuarially fair health insurance has little scope in this environment (as in Arnott and Stiglitz, 1991). Instead, subsidization primarily serves to overcome the mismatch between households' desired health budgets and the actuarially fair price of the insurance policy's generous benefits package. Our results regarding heterogeneous demand elasticities are also consistent with the importance of these two factors. According to our survey data, households headed by a widower, whose price elasticity is a multiple of that of other types of households, have considerably larger health budgets prior to our intervention and are less well informally insured. For rural households, we also explore additional economic and non-economic factors, such as exposure to health shocks, demographic structure, education and remoteness. However, we discard these as predictors for the lack of rural demand.

Our study contributes to a recent literature on microinsurance in developing countries, in which two themes have been most prominent, first, the properties of insurance demand and, second, the effects of formal insurance on production and health outcomes.[1] The two types of insurance that have by far received most attention are index-based crop insurance and health insurance. Regarding the former, important recent contributions are Giné et al. (2008), Cole et al. (2013), and Karlan et al. (2014), who find low take-up rates, of less than twenty percent, for crop insurance at actuarially fair prices in India and Ghana, respectively, but sizable price elasticities of demand. Consistent with the pattern that idiosyncratic health shocks are better insured by informal risk-sharing networks than covariate weather shocks to agricultural production (Townsend, 1994; Udry, 1994), health insurance take-up and the potential of subsidization have been found to be even lower in several middle-income country contexts (Thornton et al., 2010; Capuno et al., 2016; Levine et al., 2016; Wagstaff et al., 2016).[2]

[1] Several authors have studied the price elasticity of demand for health insurance in the United States and mostly find a fairly price-inelastic demand (Chernew et al., 1997; Blumberg et al., 2001; Gruber and Washington, 2005; Royalty and Hagens, 2005; Finkelstein et al., 2012).

[2] Capuno et al. (2016) evaluate an intervention in the Philippines, in which a fifty percent discount voucher valid for one year was bundled with an information campaign for informal sector workers in the context of an existing

We make several contributions to this literature. First, the design of our insurance policy, which is sold to individuals, combined with a detailed census of the study population allows us to identify distributional effects of insurance pricing on enrollment. In particular, we are able to disentangle household and individual enrollment, and insurance coverage within households across different age and sex groups. Our second innovation is that we identify heterogeneous demand elasticities among different subgroups of households as well as predictors of health insurance demand from extensive additional survey data. Finally, to the best of our knowledge, all existing studies of micro health insurance pricing are located in middle-income countries of Asia and Latin America, and are limited to specific sub-populations, most frequently informal workers. In contrast, Burkina Faso is one of the world's poorest countries and the insurance product is offered to the universe of households in the study district. Hence our results give a comprehensive picture of the potential of voluntary health insurance in a poor sub-Saharan African context, including the issue of adverse selection.

The remainder of this paper is structured as follows. Section 2 presents the insurance product and the subsidization intervention. We introduce the empirical methodology in Section 3. The results are discussed in Section 4 and Section 5 concludes.

2 The intervention: targeted subsidized health insurance

Burkina Faso is one of the poorest countries by international standards, with a poverty rate of 55 percent in 2009 (based on the World Bank's 2011 PPP $1.90 a day poverty line). Similarly, in 2016 it ranked fourth from the bottom in the UNDP Human Development Index. While human development indicators have improved over the last decade, neonatal and maternal mortality rates of 23 per 1,000 and 341 per 100,000 live births in 2015, respectively, are still significantly above

social health insurance program. The annual policy comes at two different prices, depending on the insuree's income, and includes full benefits for spouses and children up to age 21. The intervention covered rural and urban areas alike. They find small effects on enrollment, which increases by 3 percentage points on average. The effect is 8 percentage points larger for urban dwellers. Wagstaff et al. (2016) evaluate a similar intervention where a 25 percent discount valid for one year and an information package are randomized separately in the context of an existing social health insurance program for informal workers in two rural districts of Vietnam. There are no urban areas, where baseline enrollment is higher. The annual policy is for prime-aged adults only (excluding children and elderly) meeting certain criteria, at the individual level and involves a premium which is declining in the number of insured household members. For individual-level enrollment, which is their sole dependent variable, they find only small and statistically insignificant effects of both interventions, including the combination of the two. There is some evidence for selection on risk in that demand of ill individuals is more price-sensitive (the opposite of adverse selection in the sense of Rothschild and Stiglitz, 1976). Two further papers, Levine et al. (2016) and Thornton et al. (2010) mention similar effects of subsidization on enrollment among a subgroup of self-selected households in rural Cambodia and urban informal workers in Nicaragua, respectively. Their primary focus is on health care facility utilization and health-related household expenditures, however.

the average in sub-Saharan Africa (World Bank, 2017). The country's poor health infrastructure, reflected by a low density of primary health centers (*Centre de Santé et de Promotion Sociale*, CSPS), is widely seen as an important impediment to development. Further supply problems are absenteeism and a strong urban bias in the allocation of medical staff (*Ministère de la Santé Burkina Faso*, 2011). With no country-wide statutory health insurance in place and a negligible private health insurance market, Burkinabé usually pay for health care at the point of service. About three quarters of households' health expenditures are out of pocket, which are mostly spent on drugs (*Ministère de la Santé Burkina Faso*, 2011).

Our study area is the administrative department of Nouna in north-western Burkina Faso, a part of Kossi province bordering Mali (see Figure A1 in the Online Appendix for a map). At the time of our study, it was inhabited by a population of about 70,000 individuals of whom two-thirds live in villages and one third in and around the town of Nouna, the only urban area.[3] Given that 23 percent of Burkina Faso's population resides in urban areas (INSD, 2008), the study area's rural-urban composition is roughly representative of the country. Health shocks are a major threat to livelihoods in the region (Belem et al., 2011), while the average distance to the closest health care facility amounts to about ten kilometers, which is above the national average of 7.2 (Robyn et al., 2012).

With the objective of developing a nation-wide health insurance scheme, the Burkinabé Ministry of Health decided to explore the potential of voluntary micro health insurance during the early 2000s. The department of Nouna was chosen as the pilot site because it features a Health Research Center (*Centre de Recherche en Santé de Nouna*), which has been administering a Health and Demographic Surveillance System since 1993 (De Allegri, 2006). In 2004 the local insurance corporation *Assurance Maladie à Base Communautaire* (AMBC) was founded and the scheme was rolled out within three years, so that since 2006 every household in the department has had access to micro health insurance. Regarding the pricing of the insurance product, to enroll a household pays a one-time membership fee of CFA 200 and an upfront premium of CFA 1500 and 500 (approximately 3 and 1 US$ in 2009, not purchasing power parity adjusted, respectively) per insured adult and child, up to the age of 16, respectively.[4] Payment can take place in install-

[3] According to the 2006 Census of Burkina Faso, Nouna town is an urban locality. The national definition of "urban locality" is a "locality with 10,000 inhabitants or more and with sufficient socio-economic and administrative infrastructures" (United Nations, 2006; INSD, 2008).

[4] For comparison, the 2009 national poverty line is CFA 130,735 per person per year (INSD, Institut National de la Statistique et de la Démographie, 2015), which is a little less than the World Bank's 1990 dollar-a-day international poverty line (Ravallion et al., 1991) in the same year. According to INSD, Institut National de la Statistique et de la Démographie (2015), which also includes small-area poverty estimates, consumption poverty

ments and health insurance coverage starts from the day of the last installment, lasting for twelve months. Enrollment campaigns were carried out around the turn of the calendar year, after the harvest of the main crops when the liquidity of farmers is at a peak, with the objective of enrolling households before the onset of the monsoon in May, a time when the health environment becomes especially critical. The benefit package includes general and specialized outpatient and inpatient treatment in one of 13 primary health centers and the department's hospital in Nouna town, and generic as well as essential brand-name drugs (Fink et al., 2013).[5] To obtain benefits, each insured individual obtains an insurance card, which entitles the holder to consultations and drugs free of charge at all health centers and the hospital as per the benefits package.

Initially it was mandated that a household enrolls all its members to limit adverse selection and prevent intra-household inequalities. Due to a perception that this requirement further reduced insurance enrollment in an environment where the average household size is close to eight, households were permitted to purchase health insurance at the individual level during the period studied here (Fink et al., 2013). As a social health insurance scheme, economic self-sufficiency has not been an objective and subsidies have come from the Burkinabé Ministry of Health as well as international donors (Parmar et al., 2012).

Despite of the seemingly affordable insurance premium and the favorable benefits-to-cost ratio, by 2006 enrollment rates remained far below expectations and were especially low among poor households. To illustrate, Figure 1 graphs insurance enrollment in 2006 as a function of household wealth. We proxy household wealth by an asset index, which is the first principal component of 28 household-level indicators calculated from census variables (Filmer and Pritchett, 2001).[6] The horizontal axis of Figure 1 depicts household wealth percentiles and the vertical axis the incidence of enrollment of any household member, where an observation is a household. According to this graph, enrollment is increasing in wealth in a convex fashion. We have also included kernel density estimates of the wealth index by sector, rural versus urban. Clearly, urban households (the dashed line) possess substantially more assets than their rural counterparts (dotted line) and also account for the bulk of insurance policies sold in Nouna in that year.

evaluated at the national poverty line stood at 47 percent in the department of Nouna in the same year, which equals precisely the national figure for that year. Hence median per capita consumption in the department of Nouna is about equal to the national poverty line. Thus, in 2009 the adult premium equaled about 1.15 percent of median annual per capita consumption expenditures.

[5] Specifically, the benefit package includes comprehensive prenatal care, laboratory tests, inpatient hospital stays, X-rays, emergency surgery and transport by ambulance. It does not include dental and opthalmologic treatment, conditions of addiction, HIV Aids and other chronic diseases.

[6] Since the asset data is available only from a 2009 census, the index has to be viewed as an approximation to household wealth in 2006.

[Figure 1 about here]

Given the lack of enrollment among poor households, in 2007 we decided to offer a 50 percent discount on the insurance premium to the poorest quintile of households in each village and urban neighborhood. To identify beneficiary households for two subsequent years, we carried out community-based targeting (CBT) exercises (Alatas et al., 2012) in all villages and Nouna town during the first quarter of each of the years 2007, 2009 and 2011. Regarding the urban area, guided by local informants we partitioned Nouna town into 22 similar-sized neighborhoods of roughly ninety households (see Figure A2 of the Online Appendix for a map). The focus of this paper is on the 2009 campaign.[7]

We will now explain the targeting exercise in some detail because our experimental design crucially builds on some of the procedural details. At the outset, census lists were drawn up from the Demographic Surveillance System for all 38 villages and 22 urban neighborhoods for each community, by which we mean either a village or an urban neighborhood. In each community, the targeting exercise began with a publicly convened community meeting, where the facilitator informed about the purpose of the assembly and initiated a focus group discussion to define criteria for three to four wealth categories.[8] Next, the focus group elected three informants by acclamation. Each informant was then instructed to independently produce a wealth ranking of all households on the census list that are currently present by assigning each household to one of the previously defined wealth categories and by ordering all households within each category. Subsequently, the facilitator calculated the beneficiary contingent as one fifth of the number of ranked households. The small deviations from the twenty percent share in some communities, manifested by the standard deviation of 0.01 in Table 1, are mostly due to rounding. Importantly, the exact beneficiary contingent for the community was communicated neither to the assembly nor to the informants. Given the three wealth rankings and the beneficiary contingent, Q say, the facilitator determined the set of beneficiary households according to the following algorithm:

First, all households not ranked among the Q poorest by at least one informant are eliminated. Second, each of the remaining households is assigned to one of three groups according to the number of informants by whom it has been ranked among the Q poorest. Denoting these groups

[7] In 2007, the CBT exercises faced some implementation challenges that negatively impact the experimental design we are exploiting for the identification of causal effects of insurance pricing. Subsequent to 2009, there has been no economic census, which we use for many of our analyses.

[8] The two most often stated criteria for characterizing poverty, “has insufficient food” and “has nothing”, directly or indirectly relate to consumption and assets (Savadogo et al., 2015, p.8).

by A1, A2 and A3, the latter comprises all households ranked among the Q poorest by all three informants, A2 those ranked among the Q poorest by exactly two informants, and A1 those ranked among the Q poorest by exactly one informant. According to Table 1, the shares of these groups in all households amount to 7, 11 and 22 percent, respectively, with ample variation across communities. Third, denoting by Q_1, Q_2 and Q_3 the number of households in A1, A2 and A3, the beneficiaries are determined according to the following rule:

Case 1: If $Q_2 + Q_3 < Q$, the beneficiary set includes the union of A2 and A3, and the informants are requested to select an additional $Q - (Q_2 + Q_3)$ households from A1 in a trilateral consultation. This occurred in 35 of the 50 communities.

Case 2: If $Q_2 + Q_3 = Q$, the beneficiary set is the union of A2 and A3. This occurred in 13 of the 50 communities.

Case 3: If $Q_2 + Q_3 > Q$, the beneficiary set includes A3 and the informants are requested to select an additional $Q - Q_3$ households from A2 in a trilateral consultation. This occurred in two of the 50 communities.

[Table 1 about here]

The beneficiary lists were publicly posted a few days after the targeting exercise. On average, one targeting exercise took half a day.[9]

[9] Our design of the community-based targeting procedure was meant to balance the following three objectives. First, the process was intended to be participative, transparent, and reflect the community's social preferences. Second was the concern for cost-effectiveness and third the desire to make the procedure generate exogenous variation for an impact evaluation design. Regarding the first and third items combined, a statistical targeting method, such as a proxy-means test, or a single ranking of all households by the entire community assembly combined with a fixed beneficiary contingent (as in Alatas et al., 2012) would obviously deliver a sharp regression discontinuity design for each community, with a household's wealth rank (or score) as the forcing variable. We considered this excessively expensive, however, mainly because of the high demands on community members' as well as the facilitator's (or enumerators') time relative to the small stakes. Given the enrollment rates ex post, effective premium subsidies amounted to around twelve 2009 US dollars (not purchasing-power parity adjusted) per community. On the other hand, to meet the cost-effectiveness and evaluation concerns, a single wealth ranking by one elected informant is an obvious choice. However, we considered this too little transparent for the communities and feared a lack of legitimacy. Moreover, we expect the aggregate of multiple informants' poverty preferences to approximate social preferences more accurately. The procedure we have designed may thus be viewed as a compromise between our three principal objectives. It is, moreover, in line with other applications in sub-Saharan Africa documented in some recent articles. In particular, Temu and Due (2000) for Tanzania, Handa et al. (2012) for Malawi and Robertson et al. (2014) for Zimbabwe describe procedures similar to ours (see also Table 1 in Schleicher et al., 2016). A noteworthy difference is, however, that they all involve more (five to six) informants.

3 Empirical approach

3.1 The fuzzy regression discontinuity design

In this section we explain how the beneficiary identification algorithm of the community targeting exercise delivers a fuzzy regression discontinuity design. In a nutshell, we will show that a household's probability of being eligible for the subsidy has a discontinuity in the household's community wealth rank, a concept that we shall define shortly. This exogenous variation in eligibility facilitates estimation of intent-to-treat effects of pricing on health insurance enrollment and other outcomes within a two-stage estimation framework. We establish the discontinuity in eligibility as a function of a household's wealth rank from the mechanical rules implied by cases 1, 2 and 3 above, while the fuzziness comes from those households that obtain the beneficiary status through the consultations in cases 1 and 3. This leads to some "non-compliance" (Angrist et al., 1996) to the right and left of the discontinuity, respectively.

The most straightforward configuration is case 2, a fluke, in which all beneficiaries are determined by the targeting algorithm's mechanical rule. Denoting the wealth rank of household i, from poorest to wealthiest, assigned by informant j by rk_{ij}, consider the same household's median rank, $\widetilde{rk}_i$ say, where the median is taken over the three informants' assessments, $\widetilde{rk}_i = \text{median}(rk_{i1}, rk_{i2}, rk_{i3})$. We will call this statistic "wealth rank" in the sequel. The rule in case 2 states that a household is eligible if at least two informants have assigned a rank not greater than Q. This is equivalent to the condition that the household's wealth rank is not greater than Q. In other words, the median rank is the sufficient statistic of the three individual wealth ranks for a household's eligibility. More formally, we have that $\Pr(E_i = 1|rk_{i1}, rk_{i3}, rk_{i3}) = \Pr(E_i = 1|\widetilde{rk}_i) = \mathbb{1}\{\widetilde{rk}_i \leq Q\}$, where E_i denotes eligibility and $\mathbb{1}\{.\}$ the indicator function. Hence each of the thirteen communities under case 2 gives a sharp regression discontinuity design when the wealth rank is used as forcing variable. The discontinuity occurs at a wealth rank of Q, which we will refer to as "the cutoff". This case is depicted in panel (b) of Figure 2.

This insight guides the analysis of the remaining two cases. For case 1, $\Pr(E_i = 1|\widetilde{rk}_i)$ equals one for $\widetilde{rk}_i \leq Q$, $(Q - Q_2 - Q_3)/Q_1$ on average for $\underline{rk}_i \leq Q < \widetilde{rk}_i$, where $\underline{rk}_i$ denotes the smallest of the three ranks assigned to household i, and zero otherwise. Hence, there is some non-compliance to the rule governing case 2 in the form of "always-takers" (Angrist et al., 1996) for households ranked among the Q poorest by exactly one informant, to the right of the cutoff. According to

Table 1, the rate of non-compliance among all households to the right of the cutoff equals merely 4 and 2 percent in rural and urban case 1 communities, respectively. The shape of $\Pr(E=1|\widetilde{rk})$ as a function of $\widetilde{rk}$ for $\widetilde{rk} > Q$, and hence the extent of the discontinuity depends on the extent to which the (non-mechanic) collective consultation decision correlates with the wealth rank. For a negative correlation, which would be expected, the discontinuity will usually be decreasing in the absolute value of this correlation. An example of this case is depicted in panel (a) of Figure 2.

For case 3, $\Pr(E_i = 1)$ equals one only for $\overline{rk}_i \leq Q$, where $\overline{rk}_i$ denotes the highest of the three ranks assigned to household i, $(Q - Q_3)/Q_2$ on average for $\widetilde{rk}_i \leq Q < \overline{rk}_i$, and zero otherwise. In words, there is some non-compliance to the rule governing case 2 in the form of "never-takers" (Angrist et al., 1996) for households ranked among the Q poorest by exactly two informants, while there is full compliance to the right of the cutoff, $\Pr(E = 0|\widetilde{rk}) = 0$ for $\widetilde{rk} > Q$. According to Table 1, the rate of non-compliance among all households to the left of the cutoff equals merely 1 and 2 percent in rural and urban case 3 communities, respectively. The shape of the function $Pr(E = 0|\widetilde{rk})$ for $\widetilde{rk} \leq Q$ and hence the extent of the discontinuity at Q depends, as for case 1, on the extent to which the outcome of the trilateral consultation correlates with the wealth rank. For a negative correlation, the discontinuity will usually be decreasing in the absolute value of this correlation. An example is depicted in the panel (c) of Figure 2.

[Figure 2 about here]

Pooling the data from different communities - and hence the three cases - and normalizing the forcing variable suitably gives a fuzzy regression discontinuity design (FRD) with the normalized wealth rank as forcing variable and some non-compliers to the left and right of the cutoff. Looking at this design within a two-stage framework, the discontinuity of eligibility in the wealth rank serves as instrumental variable for the "treatment" with a subsidized premium in a second stage regression, with enrollment as dependent variable. In this second stage, two estimators are of interest in general. For most of the analysis, our focus will be on the intent-to-treat (ITT) effect, which equals the discontinuity in the conditional expected value of the outcome variable as a function of the forcing variable at the cutoff. Since the intention to treat does not have much economically meaningful content in our application, we will view this estimator in the first place as a lower bound to the average causal treatment effect at the cutoff. This bounding property holds under the plausible assumption of a monotone treatment response (Manski, 1997), which in our context says that a household is not less likely to enroll when offered insurance at the subsidized rather than the full price. Given a compliance rate of around 85 percent and the enrollment behavior of non-compliers at the cutoff, which we will show to be exclusively "always-takers" (Angrist et al., 1996) in our setting, we will argue that the intent-to-treat effect is a fairly tight lower bound to the average treatment effect at the cutoff.

The second estimator is the local average treatment effect (LATE) obtained from a two-stage-least squares regression, which gives the causal treatment effect for compliers. Here a complier is a household whose eligibility status drops from one to zero when its forcing variable crosses the threshold. Building on recent work by Bertanha and Imbens (2014), we will argue that, in our application, the ITT estimator is likely closer to the average causal treatment effect at the cutoff than the LATE.

Turning to the empirical implementation, we deal with the issue of aggregation over communities with different numbers of households by normalizing the forcing variable as follows. For each community, we transform the wealth rank to wealth rank percentiles. Second, we center the resulting variable by subtracting the community's beneficiary quota, that is the beneficiary contingent divided by the number of households on the census list. For each community with households indexed by i, where $i = 1, ..., n$, we denote the resulting normalized wealth rank by $wr_i = \left(^{\#} \left\{ j : \widetilde{rk}_j \leq \widetilde{rk}_i \right\} - Q \right) / n$, where $^{\#}\{A\}$ denotes the cardinality of the set A. Note that the range of wr is bounded by -0.2 and 0.8 for case 2 communities, while it is offset to the right and left for case 1 and case 3 communities, respectively, by the relative frequency of non-compliers.

Using local linear regression as suggested by Lee and Lemieux (2010), for the first stage we will estimate

$$e_i = a + b \cdot \mathbb{1}\{0 \leq wr_i\} + d_1 \cdot wr_i + d_2 \cdot \mathbb{1}\{0 \leq wr_i\} * wr_i + v_i, \tag{1}$$

where e_i denotes the eligibility of household i, a is an intercept term and v_i a stochastic error. The parameter d_1 gives the slope of eligibility's conditional expectation to the left and d_1+d_2 to the right of the cutoff, while b captures the discontinuity in the conditional expected eligibility. To obtain the intent-to-treat effect of subsidization on enrollment, y, the estimating equation is

$$y_{it} = \alpha + \beta \cdot \mathbb{1}\{0 \leq wr_i\} + \delta_1 \cdot wr_i + \delta_2 \cdot \mathbb{1}\{0 \leq wr_i\} * wr_i + u_{it}, \tag{2}$$

where y_{it} denotes enrollment of household i in year t. The subscript t indexes the two years 2009 and 2010, for which the vouchers that were allocated in early 2009 were valid. Keeping with standard practice of parameterizing RD regression equations, the coefficient β captures the effect of a price increase, from the subsidized to the full premium, on enrollment. Equation 2 is the reduced form estimating equation within a two-stage setup. In all estimations, we cluster standard errors at the level of the household.

As recommended in the recent methodological literature on regression discontinuity designs, inference in our RD design is based on a fully data-driven procedure. Specifically, our RD estimates are based on the bias-corrected inference procedure proposed by Calonico et al. (2014) and on fully data-driven, asymmetric bandwidth choices following recent work by Imbens and Kalyanaraman (2012) and Calonico et al. (2014). We also present various RD plots with fully data-driven choices of the number of bins in evenly-spaced partitions as proposed by Calonico et al. (2015).[10] As recommended by Imbens and Kalyanaraman (2012), we use a triangular (or edge) kernel throughout.

3.2 The different layers of insurance demand

In this section we develop an accounting framework linking the different facets of insurance demand. We will show how individual and household-level demand are related and motivate the choice of dependent variables for the subsequent empirical analyses of price elasticities accordingly.

An obvious object of interest is demand at the individual level, which we will denote by $\Pr(Y_{ij} = 1|p)$ in a statistical population model, where i indexes household and j the individuals in that household. The dummy variable Y_{ij} equals one if individual ij is enrolled. By the dummy variable Y_i we denote the incidence that a household makes use of the scheme, more precisely that at least one member of the household is enrolled. We call $E(Y_i)$ the extensive margin of demand and the intensity of individual insurance within an insured household, $\Pr(Y_{ij} = 1|Y_i = 1)$, the intensive margin. We denote by p the premium and by S_i the size of a household (as a random variable). We show in the Appendix that

$$\frac{d \log [\Pr(Y_{ij} = 1|p)]}{d \log p} = \frac{d \log [\Pr(Y_{ij} = 1|p, Y_i = 1)]}{d \log p} + \frac{d \log [E(S_i|p, Y_i = 1)]}{d \log p} + \frac{d \log [\Pr(Y_i = 1|p)]}{d \log p}. \tag{3}$$

In words, the price elasticity of demand at the individual level equals the sum of the price elasticity at the extensive margin (the last term on the right hand side), the price elasticity at the intensive

[10] We carry out all estimations with the statistical software package Stata and employ the RD package by Calonico et al. (2014), which comprises the three commands `rdrobust`, `rdbwselect`, and `rdplot` for RD estimates, bandwidths, and plots, respectively.

margin (the first term on the right hand side), and the relative change in the average size of insured households. In our empirical analysis we will estimate the four terms in turn to obtain a comprehensive picture of how a price change impacts demand. For demand at the individual level the estimation sample is the universe of individuals and the dependent variable individual enrollment. For demand at the intensive margin the dependent variable is the same, while the estimation sample is restricted to all individuals in households where at least one member is enrolled. For the extensive margin, the estimation sample is the universe of households and the dependent variable a dummy indicating whether any member of the household is enrolled. Finally, the second term on the right hand side is identified by a regression in which each insured household is one observation and the dependent variable the household's size.

4 Empirical analysis

4.1 Data and descriptive statistics

The data for our main empirical analyses involve no sampling. Instead, we conduct all our analyses with the universe of households participating in the community wealth rankings. We merge the following four data sources by household identities: wealth rankings and beneficiary lists from the targeting exercise, administrative data on insurance enrollment and benefits from the health insurance provider, and demographic characteristics of households and individuals from a demographic census, which is updated every three months. For further analyses, we use, in addition, information on household wealth and occupations from a household economic census canvassed in 2009, contemporaneous with the community targeting exercise.

For each household, the wealth ranking data contain the wealth ranks assigned by the three informants as well as the final eligibility status in 2009. We use the former to construct the forcing variable of our fuzzy regression discontinuity design and the latter as the dependent variable in our first stage estimations. Administrative records from the health insurance provider contain individual annual information about health insurance enrollment and benefits. The former is our main outcome variable of interest, while we use health insurance benefits as dependent variable to explore adverse selection. Information from the demographic census allows us to identify intra-household allocations of enrollment, in particular across age and sex groups of household members. In further analyses of insurance demand, we construct a household wealth index from 28 variables on dwelling characteristics and asset possessions obtained from the economic census (Filmer and Pritchett, 2001).

Table 2 contains descriptive statistics for the merged dataset at the individual and household level. For enrollment, we pool the years 2009 and 2010, for which the voucher has been valid. We report mean values for the entire study area and for rural and urban sectors separately. In addition, we report means also for the subgroup of cutoff households, whose normalized wealth rank is within a five percentile range (one-sided) around the eligibility cutoff.

[Table 2 about here]

Our data cover 35,700 individuals, who form close to 5,000 households.[11] According to the figures set out in Table 2, education levels are low and households primarily rely on agricultural activities for income generation, even in the urban sector. In line with the large urban-rural divide with respect to wealth, which is depicted in Figure 1, urban households have more education and the household head's primary occupation is more often non-agricultural. With 5.8 members, cutoff households are substantially smaller, by 1.7 or 23 percent, than the average household. In the urban sector, they also have a significantly higher share of elderly and fewer children. Almost every other urban cutoff household is headed by a widow or widower. For insurance enrollment at the extensive margin, enrollment rates in 2009 and 2010 average at six and fifteen percent in rural and urban areas, respectively. Individual enrollment has stood at three and nine percent, respectively. The average insurance benefit for individuals in cutoff (all) households equals CFA 2,753 (CFA 3,525), a little less than twice the regular adult insurance premium of CFA 1,500. These figures illustrate that the insurance scheme is heavily subsidized even at the policy's regular price, which falls far short of the actuarially fair price.

We shall close this section with a brief discussion of the living conditions of households close to the cutoff in our regression discontinuity design. We approach this issue by proxying a household's position in the distribution of per capita consumption, on which we lack data, by its position in the distribution of our asset-based wealth index and combining this with official national and regional consumption poverty estimates (INSD, Institut National de la Statistique et de la Démographie, 2015), which let us infer that median per capita consumption in the department of Nouna is close to

[11] The difference to the earlier-mentioned total population figure of 70,000 is due to two reasons. First, the census lists used for the community targeting exercises were not fully up-to-date, that is some households on the lists had seized to exist at the time of the targeting exercise, while some recently established households were not included on the lists. Second, households on the census lists that were not present in the community at the time of the CBT exercise were not included in the wealth rankings.

the national poverty line (see footnote 4). Given the urban and rural wealth distributions in Figure 1, the upper end of the lowest quintile of the urban distribution is located close to the median of the aggregate distribution. Hence, we expect the average urban household's consumption at the cutoff to be close to Burkina's national poverty line and thus moderately poor by national as well as international standards. This assessment is also broadly consistent with the national urban consumption poverty rate of 23.7 percent for 2009 (INSD, Institut National de la Statistique et de la Démographie, 2015). For the rural areas, on the other hand, the corresponding percentile is less than 20, implying that a rural household at the cutoff is poorer than the median poor household in the Nouna department. Given that, according to INSD, Institut National de la Statistique et de la Démographie (2015), consumption of poor households in the Nouna department falls short of the national poverty line by 30.6 percent on average, a rural household at our eligibility cutoff is likely ultra-poor by international standards. This assessment is also broadly consistent with the national rural consumption poverty rate of 54 percent (INSD, Institut National de la Statistique et de la Démographie, 2015).

To summarize, urban households in our context are significantly wealthier than their village counterparts. Moreover, they have shorter distances to the health care facilities that are part of the insurance package, and more experience with markets and formal market institutions. On these grounds, heterogeneity in insurance demand across the two sectors is very likely. We shall therefore present all our results separately for rural and urban households.

4.2 Main results

Targeting of vouchers

For both rural and urban communities, Figure 3, which graphs the regression function given in (1), confirms that the sign of a household's normalized wealth rank is a strong predictor of eligibility for a voucher. The plots demonstrate that virtually all households with a negative normalized wealth rank are eligible for the subsidy, especially in the urban areas. In other words, never-takers are of little concern in our subsequent analyses of enrollment. In contrast, just to the right of the cutoff, about fifteen percent of households are eligible and hence non-compliers. These always-takers account for most of the fuzziness in our regression discontinuity design. Still, the discontinuity equals about 85 percentage points in rural and urban communities alike.

[Figure 3 about here]

Health insurance enrollment

The first three columns of Table 3 contain estimates of the extensive margin intent-to-treat effects of the subsidy, β in (2), for different sub-samples. In addition, panel (b) of Figure 4 plots health insurance enrollment at the household level over the normalized wealth rank, the forcing variable, for the urban sector. According to column 1 of Table 3, we find a positive, statistically significant effect of 10.6 percentage points for the pooled sample. Columns 2 and 3 reveal that this effect is almost exclusively driven by urban households' demand, where the share of enrolled households increases from ten to 35 percent, implying a price elasticity exceeding one.[12] While enrollment of rural households at the regular price is around one third that of urban households, the effect of subsidization is less than a tenth and statistically insignificant (see also panel (a) in Figure 4).

[Figure 4 about here]

[Table 3 about here]

Before continuing with further results, we shall briefly discuss one aspect of the external validity of our estimates, the counterfactual identified by the point estimates in our application. Following Bertanha and Imbens (2014), Figure 5 plots the estimated regression function of (2) for the subsample of eligible households by sector. Hence panel (b) of this figure corresponds to panel (b) of Figure 4 with the difference that only eligible households are included. When never-takers play only a negligible role as in our context, the results of Bertanha and Imbens (2014) together with a monotone treatment response assumption (Manski, 1997) imply that the average treatment effect (ATE) at the cutoff corresponds to the LATE when there is no jump in enrollment among eligible households. On the other hand, the ATE is larger than, but close to the ITT (as in a sharp RDD) when enrollment of households with a voucher to the right of the cutoff is close to zero. Clearly, for urban households, the situation depicted in panel (b) of Figure 5 is closer to the latter than the former scenario. According to Table 4, the discontinuity among households with vouchers equals 27.2 percentage points, which is - albeit imprecisely estimated - very close to the 25.2 in column 3 of Table 3.[13] This pattern is robust as it also occurs for subgroups of households that we will discuss shortly. In our context this means that the price sensitivity of households which

[12] We calculate the price elasticity as the change in demand relative to average insurance demand at the cutoff.

[13] We manually set the bandwidths for this exercise equal to the bandwidths obtained automatically in the respective columns of Tables 3 and 5 as the automatic bandwidth algorithm of Calonico et al. (2014) does not converge with the unbalanced data used in the estimations suggested by Bertanha and Imbens (2014).

obtain a voucher as a consequence of a consultation among the three informants is much smaller, and in fact almost negligible, than for a randomly selected household at the cutoff. According to Bertanha and Imbens (2014), in this case the ITT estimate is a fairly close lower bound to the ATE at the cutoff and we will hence restrict our attention to the reduced-form estimating equation 2 for the remainder of the analysis.

[Table 4 about here]

[Figure 5 about here]

Columns 4 to 6 of Table 3 contain ITT estimates for individual enrollment. The estimating equation is

$$y_{ijt} = \alpha + \beta \cdot \mathbb{1}\{0 \leq wr_i\} + \delta_1 wr_i + \delta_2 \cdot \mathbb{1}\{0 \leq wr_i\}\ wr_i + u_{ijt}, \tag{4}$$

where j indexes individuals within household i. We continue to cluster standard errors at the level of households. Analogous to the extensive margin results, among cutoff households the fraction of insured individuals increases from 5.6 to 23 percent in urban areas (see also panel (a) of Figure 6), while there is only a small and insignificant increase for rural residents. Column 7 of Table 3 and Figure 6b give the RD estimate for the intensive margin of enrollment for urban households. To be precise, we estimate equation 4 only with individuals from (partially or fully) insured households. A negative value of β implies that the subsidy increases health insurance coverage within insured households. While average coverage within insured urban households at the cutoff stands at around seventy percent according to panel (b) of Figure 6, we do not find any intensive margin effect of subsidization. The same applies to the size of insured households in urban areas: according to panel (c) of Figure 6, the average insured urban household at the cutoff has around 5.5 members (the same as among all cutoff households; see Table 2) and subsidization has no selection effects concerning household size.[14] The findings thus far obtained imply that both the first and the second term on the right hand side of (3) are close to zero; hence individual and household-level insurance demand have similar elasticities. As a consequence, the absolute increase in individual demand of 17.4 percentage points equals precisely the extensive margin increase of 25.2 percent times the intra-household coverage rate among individuals in insured households of about .7 at the cutoff.

[Figure 6 about here]

[14] Because of the negligible enrollment rates we do not report intensive margin and selection analyses for rural households. The estimates are all small and statistically insignificant.

To assess the overall effect of subsidization on enrollment among urban households, Figure 7 depicts extensive-margin enrollment across the whole urban wealth distribution. On both sides of the cutoff, we perform locally weighted scatterplot smoothing to obtain average conditional enrollment rates. The plot shows that subsidization puts enrollment among the poorest quintile of households on par with households in the wealthiest quartile. Hence, at least in the urban context, targeted subsidies successfully enhance equity in the access to formal insurance.

[Figure 7 about here]

Selection into health insurance

Information from the detailed demographic census allows us to explore heterogeneous demand elasticities of household subgroups. For example female-headed households have been found to be more vulnerable to idiosyncratic shocks in several contexts (Mitra et al., 2016; Akampumuza and Matsuda, 2017) and could, in this case, benefit from formal insurance disproportionately. Moreover, at the individual level, we can explore differences in coverage across age groups and sex caused by subsidization. We restrict these analyses to the urban areas, where insurance demand among cutoff households is sufficiently price-elastic.

Table 5 disaggregates the extensive margin effect of subsidization (set out in column 3 of Table 3) by household head characteristics. In particular, we distinguish households headed by a married male, "regular households" for short, which account for 54 percent of cutoff households (see Table 2), from households headed by a widowed male (17 percent) or female (28 percent). In our study context, the latter group and the set of female-headed households are almost identical as there are only two households headed by a married female. The point estimates set out in columns 1 through 3 reveal a striking pattern: while insurance demand at the regular price is low and very similar across the three groups of households (according to the means reported in the third row), the price elasticity of widower-headed households is more than three times that of the other two groups of households. The demand increase among widower-headed households of 61.9 percentage points equals two and a half times the average effect reported in Table 3, while the price responsiveness of female-headed as well as regular households falls short of the average effect by one fifth and one third, respectively. Hence subsidization gets close to universal coverage among the subgroup of widower-headed households: our estimates imply a coverage rate (at the extensive margin) of close to 75 percent among subsidized households of this type. Moreover, while the semi-parametric estimation procedure which we employ does not allow for a simple test of equality of heterogeneous effects, the difference between the respective point estimates well exceeds two standard errors.

[Table 5 about here]

In columns 4 to 7 of Table 5 we explore heterogeneous effects by the household head's age. We find a large difference, of 24 percentage points, between elderly and prime-aged male household heads. Overall we conclude that both widowerhood and the household head's age are predictors of price responsiveness. As for the full sample, columns 3 to 5 of Table 4 confirm that the local average treatment effect is not a suitable estimator of the average treatment effect at the cutoff as the discontinuities in the subsamples remain large and similar in magnitude to the ITT effects when only households eligible for the subsidy are included in the estimation.

The selection into insurance on demographic characteristics at the level of households has important consequences for the distribution of insurance coverage in the population. Figure 8 demonstrates that, compared to regular households, widower-headed households have substantially higher shares of elderly and smaller shares of children and adolescents (aged 16 and younger), while the fraction of prime-aged adults, which we define to be between 17 and 55 years old, is similar. In line with this pattern, the results set out in Table 6 show that, at the individual level, elderly household members benefit disproportionately from subsidization with coverage increasing from around five to close to 50 percent. Consistent with the extensive margin selection, the principal beneficiaries are elderly individuals in widower-headed households, for whom enrollment increases by 82 percentage points, while elderly in female-headed households enjoy increases of only 32 percentage points.[15] Enrollment rates of children and adolescents increase less than the average of 17.4 percentage points (column 6 of Table 3), while prime-aged adults enjoy enrollment gains similar to the average. Across all age groups, there are no gender biases in individual enrollment, irrespective of the insurance price. Combining these findings with the extensive margin selection discussed previously, these heterogeneous individual-level effects of subsidization for different age groups are consistent with the extensive-margin selection effects rather than age-specific selection on the intensive margin.

[Figure 8 about here]

[Table 6 about here]

[15] These two figures are not displayed in the tables.

Selection into insurance according to unobserved individual risk has stimulated a large body of theoretical and empirical research.[16] In the context of a single health insurance policy that gives customers no choice except to take it or leave it, adverse selection means that the risk in the pool of individuals who enroll increases with the offer price, which will in general lead to an insurance market failure (Rothschild and Stiglitz, 1976). Similar to Polimeni and Levine (2011) and Fischer et al. (2016), we conduct such a "price test" to explore the possibility of adverse selection in health insurance demand by comparing average ex-post insurance claims across different insurance offer prices. To be precise, we use annual individual insurance claims as the dependent variable in (4) and our estimation sample contains only insured individuals. We conduct this analysis with and without observable individual characteristics, which are age-group and sex dummies in our case. When the insurer observes just these characteristics, an estimation with controls will identify the extent of pure adverse selection stemming from information asymmetries in the market. With no controls, the estimate of β in (4) will yield the compound effect of selection into insurance on observable and unobservable risk. In addition to the value of insurance claims, which we calculate conservatively as the cost of prescriptions and a flat consultation fee, we also consider the number of health care facility visits per year.

For urban households, the results are set out in Table 7 and illustrated in Figure 9. According to columns 2 and 4, where demographic controls are included, we find no evidence for selection into insurance according to unobserved risk. In fact, claims are estimated to increase by about fifteen percent under the subsidization regime. While this effect is imprecisely estimated, its sign is opposite to adverse selection, where a higher price attracts higher risks. When no controls are included, the point estimate for insurance claims increases, indicating that selection on observables goes into the same direction as selection on unobserved risk. The implied direction of the selection on observable characteristics is in line with our previous finding that disproportionately more elderly, who face greater health risks, insure when offered a discount. For health care facility visits, we find even smaller point estimates in relative terms. Nonetheless, selection on observables goes in the direction as for insurance claims.

[Figure 9 about here]

[Table 7 about here]

[16] See Cohen and Siegelman (2010) for a survey of the empirical literature on adverse selection in insurance markets in high-income countries. For health insurance they report mixed findings. For developing countries, on the other hand, empirical evidence on this matter is, as of yet, scarce (Fischer et al., 2016).

4.3 Determinants of health insurance demand

Our results thus far show that subsidization of health insurance has only a limited effect on demand among poor households, with the exception of a rather small, specific subgroup. Most notably, demand is very low in rural areas, even with a fifty-percent subsidy. While our research design does not feature experimental variation beyond the offer price, in this section we seek to explore factors that are likely responsible for this lack of demand and price sensitivity. Guided by our findings regarding heterogeneous effects, we will focus on two types of comparisons, first between rural and urban households and second across urban households by sex and marital status of the household head. In these analyses, we employ data from the 2009 economic census mentioned earlier as well as from a household panel data set covering 340 rural and 225 urban households, which were interviewed annually between 2006 and 2009. Importantly, the panel data include information on illness, health-related expenditures, and informal transfers.

Lack of demand by rural households

We first deal with the sluggish demand among rural households and explore whether rural-urban differences in the burden of disease may be driving the demand patterns we observe. According to panel (a) of Figure 10, which visualizes data from the household survey for all households with a normalized wealth rank of less than 0.2, adults in rural households face a higher burden of disease as measured by the incidence of severe illness: more than three percent of rural adults experienced a severe illness during the 30 days preceding the interview, while this figure stands at only two percent in the urban areas. With a p-value of 0.03, this difference across the two sectors is statistically significant.[17] Hence we can safely rule out a differential exposure to illness as a driver of the lack of rural demand.

On the other hand, there is a large difference in health-related out-of-pocket expenditures across the two sectors with rural and urban cutoff households spending 360 and 720 CFA per adult and month, respectively. As a consequence, the subsidized insurance premium of CFA 750 per adult roughly matches urban households' health budgets while it vastly exceeds rural dwellers' ordinary health expenditures.

[Figure 10 about here]

We now investigate the role of wealth in more detail. In this connection, a limitation of our research design is that we do not observe the price elasticity of demand along the entire wealth distribution

[17] Standard errors are clustered at the level of the household.

in each community. Hence, we cannot hold wealth constant and interact our treatment effect with a rural dummy. Instead, our estimates are local in the sense that they refer only to cutoff households. We exploit, however, the fact that the cutoff is at the same relative position in each community and that there is natural variation in wealth across communities. Along these lines, Figure 11 plots RD estimates community by community over a normalized community-wise household asset index obtained from principal component analysis, $\widetilde{w}_c$, where c indexes communities. The index is calculated such that it proxies the wealth of a cutoff household in community c.[18] According to the plot, and consistent with Figure 1, rural cutoff households command substantially less wealth than their urban counterparts. And while there is a small positive correlation between wealth and the size of the RD estimate in urban areas, such a correlation is completely absent in the villages. This motivates the following interacted estimating equation:

$$\begin{aligned} y_{cit} &= \alpha + \beta_0 \cdot \mathbb{1}\{0 \leq wr_{ci}\} + \beta_2 \cdot wr_{ci} + \beta_3 \cdot \mathbb{1}\{0 \leq wr_{ci}\} * wr_{ci} \\ &\quad + \delta_1 \cdot \widetilde{w}_c + \delta_2 \cdot \mathbb{1}\{0 \leq wr_{ci}\} * \widetilde{w}_c \\ &\quad + \gamma_1 \cdot rural_c + \gamma_2 \cdot \mathbb{1}\{0 \leq wr_{ci}\} * rural_c + v_{cit}, \end{aligned} \tag{5}$$

where y is household enrollment at the extensive margin. This equation allows us to estimate whether wealth differences alone explain the low demand elasticity in rural areas or whether there are rural demand impediments beyond wealth.

[Figure 11 about here]

According to the results, which are set out in column 1 of Table 8, almost the entire difference in the price elasticity of demand between rural and urban areas is accounted for by the parameter γ_2 (the Rural*Subsidy eligibility interaction in column 1 of Table 8), whose p-value is 0.12, while the point estimate of δ_2 is very close to zero and far from being statistically significant. With an analogous methodology, we explore differences in household size, which we take as a proxy for the within household diversification of risk, literacy, and remoteness, as measured by the distance from the next medical facility, as predictors of the demand elasticity. According to columns 2 through 4, however, none of these factors successfully explains differences in enrollment across

[18] To measure household wealth, we first calculate a wealth index for each household in the study area as the first principal component of 28 indicators of dwelling characteristics and asset possessions, surveyed in the second half of 2009 (Filmer and Pritchett, 2001). We then sort all households by this index to obtain aggregate, wealth percentiles for each household. We then sort households community by community, again by the asset index, and identify the household at the top of the first, that is poorest, quintile. We take that household's aggregate wealth percentile as a proxy of household wealth around the cutoff in community c.

communities. Instead the estimate of γ_2 becomes even more significant.

[Table 8 about here]

We also explore the possibility of better risk sharing in rural than in urban communities. Towards this, panel (c) and (d) of Figure 10 plot various measures of transfers received by adult members of the household in the five months preceding the interview. According to these figures, by all measures, urban cutoff households are more active regarding informal transfers, which suggests that informal risk-sharing is no better for rural than for urban households. To conclude, this somewhat informal analysis suggests that there are important non-economic obstacles to the dissemination of health insurance in rural areas beyond wealth, remoteness and literacy. A lack of trust in or experience with formal economic and health care institutions is an obvious remaining candidate reason in this context (Zhang et al., 2006; Basaza et al., 2008; Giné et al., 2008; Cole et al., 2013).

Demand heterogeneity among urban households

We now explore differences between widower-headed and other households for understanding the stark differences in their responsiveness to health insurance pricing. According to Figure 8 and Figures 12 through 13, widower-headed households are relatively small, wealthy (regarding assets), old (with respect to the age of their members), and literate. According to panel (a) of Figure 14, they face a high burden of disease and, with about 960 CFA per adult, have by far the largest health budgets. Moreover, according to panel (d) of Figure 14, they have somewhat less access to informal risk sharing than other households.[19] While these factors have been found to be positive predictors of health insurance demand in other contexts previously (Eling et al., 2014), a novel finding of our study is that a household's health budget and access to informal risk-sharing are especially important predictors of the price sensitivity of demand rather than its level at the regular price. Consistent with our finding on the lack of demand in rural areas, households' health budgets are a particularly strong predictor for the price-responsiveness of demand: in both comparisons that we have considered here, the subgroups with the largest health budgets are far more likely to respond to vouchers. An implication of this pattern is that the generous benefits included in the insurance package appear to be of limited importance for households' enrollment choices. Notice that, according to Table 2, individual insurance benefits average around CFA 3,000, which is more than three times urban adults' average out-of-pocket expenditures. Instead, our findings suggest that insurance pricing has to take into account households' previous health budgets. Insurance

[19] Confidence intervals and p-values are obtained with standard errors clustered at the household level.

premiums exceeding households' health expenditures in the absence of formal insurance appear to have little potential to expand insurance outreach noticeably - even if highly subsidized.

[Figure 12 through 14 about here]

4.4 Robustness checks

In this section we discuss the internal validity of our estimates and test two fundamental identifying assumptions of regression discontinuity designs in our context: first, that each subject must not be able to manipulate either her value of the forcing variable nor the threshold and, second, that the expected value of the outcome of interest absent the treatment is continuous in the forcing variable (Lee and Lemieux, 2010). Regarding the first item, no manipulation of the cutoff follows from the fact that the beneficiary contingent was fixed exogenously and not disclosed before the completion of the wealth rankings. Similarly, no sorting around the threshold follows from our procedural rules by which informants carried out the wealth rankings in seclusion and separately from each other and by neither telling the community nor the informants the beneficiary contingent. Hence, neither a household nor an individual informant had any opportunity to sort a particular household deliberately around the cutoff. In addition, as recommended by Lee and Lemieux (2010), we examine the continuity of the density of the forcing variable at the cutoff in Figure 15 for urban households. In line with the identifying assumption, the local polynomial density estimator (Cattaneo et al., 2017) exhibits no statistically significant discontinuity at the cutoff.

[Figure 15 about here]

The second fundamental assumption is that the expected value of the outcome of interest absent the treatment is continuous in the forcing variable (Lee and Lemieux, 2010). In line with common practice, we test this assumption in two ways. First, we conduct placebo experiments by employing enrollment data from years preceding our 2009 intervention. Second, we carry out balancing tests of several covariates from the demographic census. For the placebo experiment, we estimate (2) with the modification that the dependent variable is lagged by two years, that is we regress household enrollment in 2007 and 2008 on the household's normalized wealth rank in 2009. The results are plotted in Figure 16 and set out in columns 1 through 3 of Table 9. There are only very small and statistically insignificant placebo effects, which gives support to the identifying assumption.

[Figure 16 about here]

[Table 9 about here]

For the balancing tests, we test whether household characteristics surveyed contemporaneously to the community targeting exercise exhibit a discontinuity at the cutoff of the normalized wealth rank (McCrary, 2008; Lee and Lemieux, 2010). To be precise, we estimate (2) with the dependent variables household size, sex composition, literacy and principal occupation of the household head. According to the results, set out in columns 4 to 7 of Table 9, none of these covariates jumps significantly at the cutoff. As recommended by Lee and Lemieux (2010), we also explore some further alternative specifications of our basic estimating equation (2), in particular local quadratic rather than local linear regression, symmetric rather than asymmetric data-driven bandwidth choice, rectangular rather than triangular kernel and inclusion of controls, including community fixed effects. None of these modifications changes the general pattern of our main results. For considerations of space, these analyses are not shown here and available from the authors on request.

5 Conclusion

Around the globe, micro health insurance programs face the challenge of low enrollment rates, especially among the poor (Eling et al., 2014). With an original fuzzy regression discontinuity design, we have evaluated the impact of a targeted 50 percent subsidy on the take-up of micro health insurance in Burkina Faso. We have found that halving the insurance premium more than triples enrollment among poor urban households, while this intervention has been largely ineffective for rural households. A similar, but less stark pattern has been found by Capuno et al. (2016) in the Philippines. While they attribute the lack of rural demand to higher transactions costs due to remoteness, we find no evidence for this channel in our setting. Among urban households we have found that subsidization attracts almost exclusively households headed by widowers, while insurance penetration within households remains unchanged. Correlating these heterogeneous effects with background information on household health budgets prior to the intervention, as well as informal transfers, the patterns we find are consistent with two important and thus far little explored challenges that micro health insurance faces in low-income environments. First, a one-size-fits-all insurance policy with a defined benefits package and a uniform price appears to be unable to meet households' varying health expenditure goals. Second, informal risk-sharing between households appears to reduce the demand for actuarially fair insurance to close to nil. When informal risk-sharing networks succeed in insuring idiosyncratic risks effectively (as found by Townsend, 1994, and Udry, 1994), fairly priced formal insurance has little scope for improving financial protection. In contrast, all households with average health budgets smaller than the insurance premium will find health insurance unattractive. In such a case, subsidization will merely compensate for the mismatch between desired health budgets and the insurance premium. This challenge does not exist for the other thus far most popular form of microinsurance, index-based crop insurance. First, the amount of insurance that can be purchased by a farmer is variable and can be adjusted to farm size. Second, informal risk-sharing has been shown to be largely ineffective for aggregate weather shocks (Townsend, 1994; Udry, 1994). On the downside, unlike health insurance, index insurance features basis risk, a mismatch between crop losses and insurance payouts, albeit informal risk-sharing networks appear to mitigate such basis risk to some extent (Mobarak and Rosenzweig, 2013; Dercon et al., 2014). Substantiating the patterns that our data suggest within a fully experimental research design, e.g. by offering policies with different benefit packages, seems a promising direction for future research.

We end this paper with a brief remark on the direction social health insurance has taken in Burkina Faso since 2010. Due to the persistence of low enrollment rates, a lack of government funding and administrative challenges, the pilot scheme investigated here was abandoned in 2012, after another round of community targeting exercises and vouchers in 2011. In 2015, after the national parliament had passed a bill towards introducing universal health insurance in the entire country, the Nouna pilot scheme has been revived and even expanded in territorial coverage, albeit under a different implementing agency, the *Association Songui Manégré - Aide au Développement Endogène* (ASMADE). At the same time, under the *Programme Gratuité*, the Ministry of Health has generally abolished fees for maternal and child health care services (*Ministère de la Santé*, 2006) and is currently experimenting with a performance-based financing scheme for public health centers and hospitals to improve health care provision (Ridde et al., 2018).

Appendix

We consider the case where individual insurance at a uniform price p is offered to a population of size n, where n is large. We start out with an application of Bayes' rule,

$$\begin{aligned}\Pr(Y_{ij} &= 1|p) = \Pr(Y_{ij} = 1|p, ij \text{ belongs to an insured hh}) \Pr(ij \text{ belongs to an insured hh}|p) \\ &= \Pr(Y_{ij} = 1|p, Y_i = 1) \frac{E(S_i|p, Y_i = 1)}{E(S_i)} \Pr(Y_i = 1|p),\end{aligned}$$

where $E(S_i)$ denotes the mean household (hh) size in the population. To establish the second equality, notice first that "$Y_{ij} = 1|p, ij$ belongs to an insured hh" and "$Y_{ij} = 1|p, Y_i = 1$" are identical events. Second, to see that $\Pr(ij$ belongs to an insured hh$|p)$ equals $\frac{E(S_i|p,Y_i=1)}{E(S_i)} \Pr(Y_i = 1|p)$, consider the sample counterpart of $\Pr(ij$ belongs to an insured hh$|p)$,

$$\frac{\text{individuals in insured hhs}}{n} = \frac{\overline{s}^{ins}(p)}{\overline{s}} \frac{hh^{ins}(p)}{hh},$$

where $\overline{s}^{ins}(p)$ denontes the mean household size of an insured household given p, $hh^{ins}(p)$ the number of insured households given p, $\overline{s}$ the average (unconditional) household size, and hh the number of households. Clearly, the right hand side of this equation converges in probability to $\frac{E(S_i|p,Y_i=1)}{E(S_i)} \Pr(Y_i = 1|p)$, which establishes the claim. Taking logarithms and differentiating with respect to the logarithm of p completes the proof.

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Figures and Tables

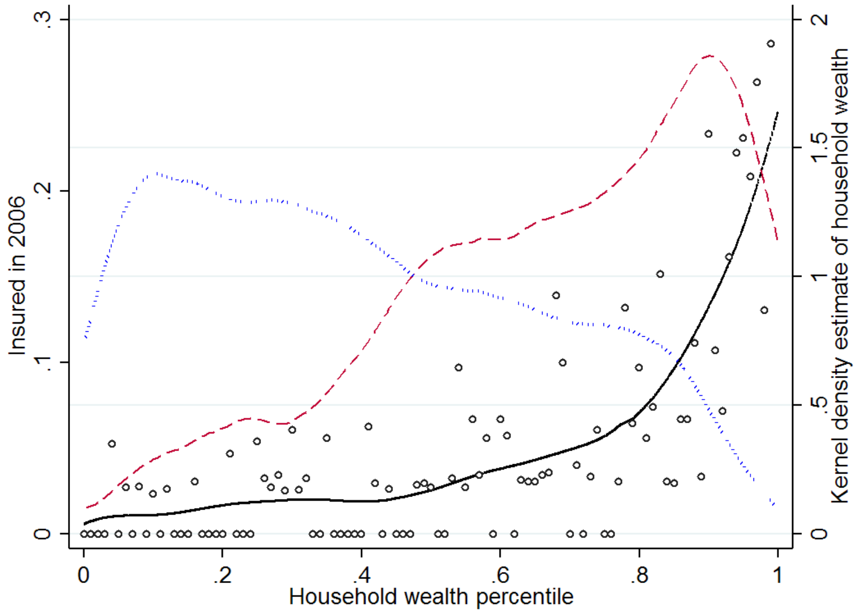
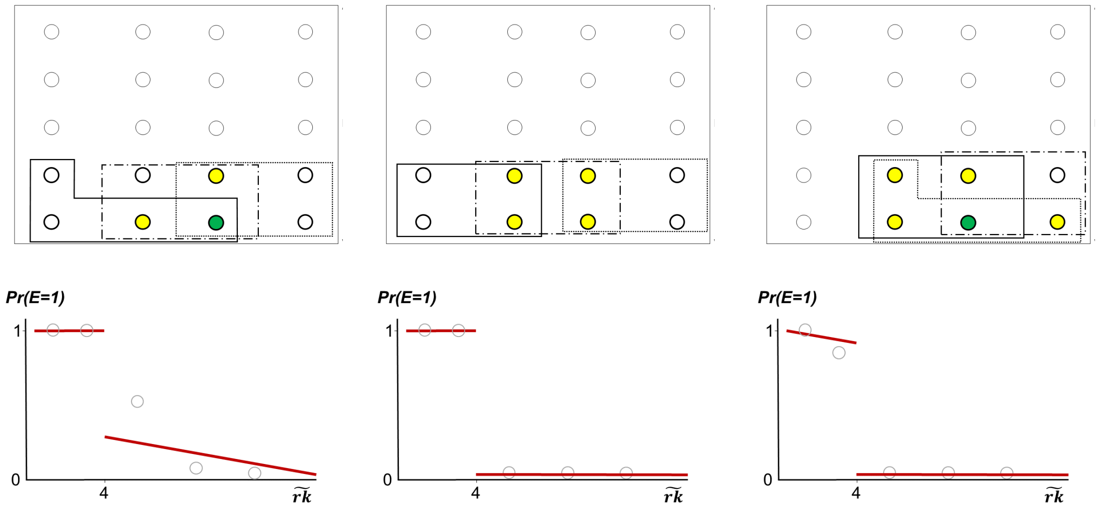


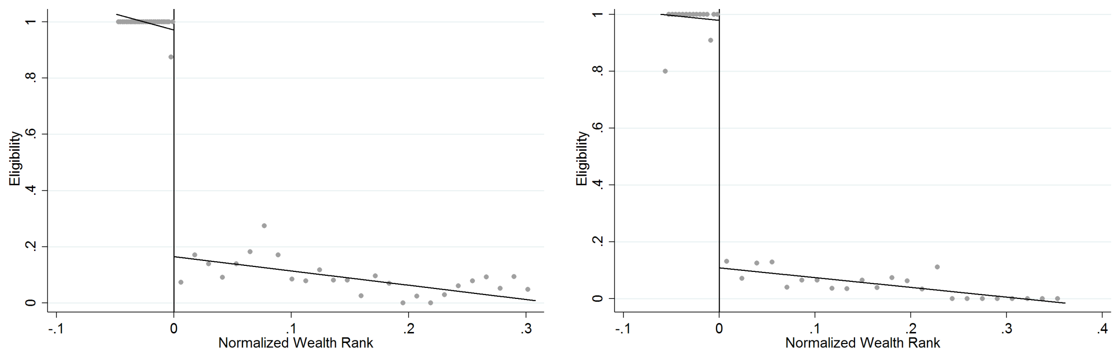
Figure 1: Enrollment prior to subsidization

Notes: Dots depict households' average insurance enrollment in 2006 by wealth percentile. Household wealth is calculated as an asset index constructed with principal component analysis (Filmer and Pritchett, 2001) from 2009 census data. The solid line depicts the relationship between household wealth and insurance enrollment using locally weighted regression. The dotted and dashed lines depict kernel density estimates of household wealth for the rural and urban sector, respectively.



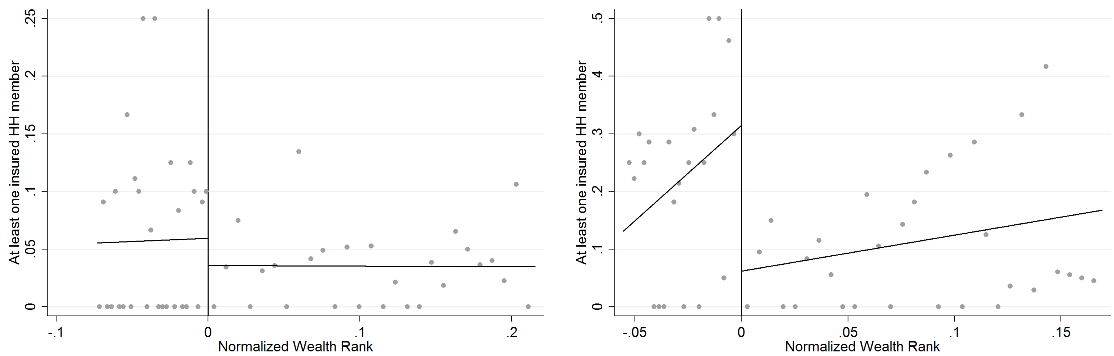
(a) Case 1: $Q > Q_2 + Q_3$ (b) Case 2: $Q = Q_2 + Q_3$ (c) Case 3: $Q < Q_2 + Q_3$

Figure 2: The community-based targeting algorithm as regression discontinuity design



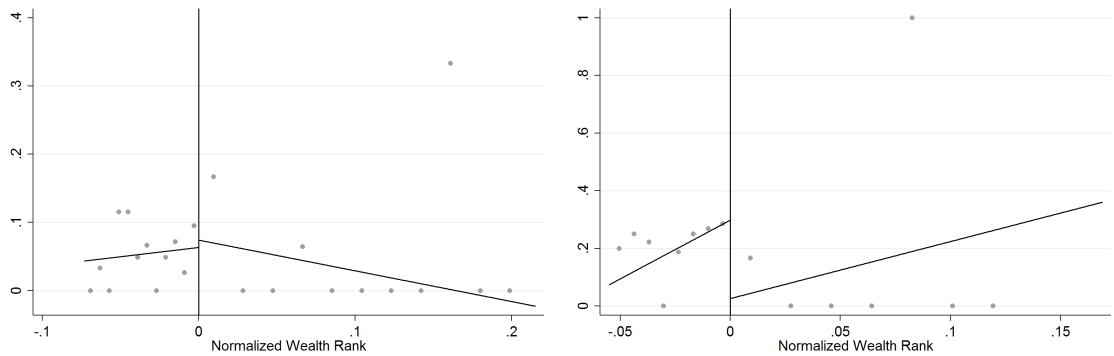
(a) Rural (b) Urban

Figure 3: Normalized wealth rank and eligibility



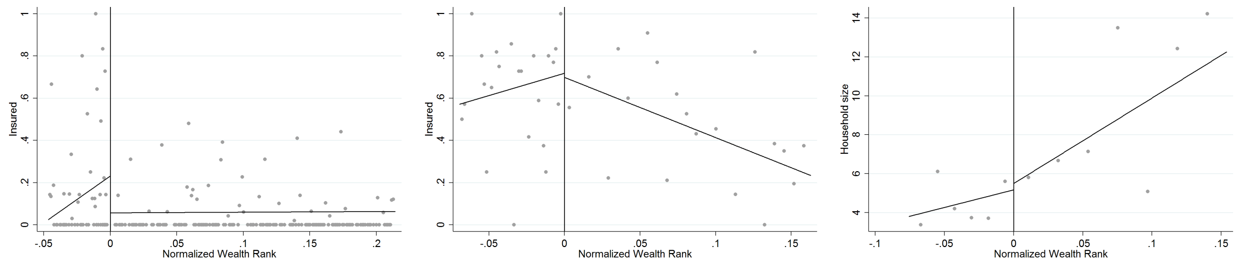
(a) Rural (b) Urban

Figure 4: Demand for health insurance, extensive margin, by sector



(a) Rural (b) Urban

Figure 5: Demand for health insurance among eligible households, extensive margin, by sector



(a) Population (b) Intensive margin (c) Household size

Figure 6: Demand for health insurance, urban sector

Figure 7: Enrollment along the wealth distribution, extensive margin, urban sector

Notes: Enrollment data comes from administrative insurance records in 2009 and 2010. The normalized wealth rank is calculated from the 2009 community-based targeting exercises. The fitted line is obtained from a locally weighted regression.

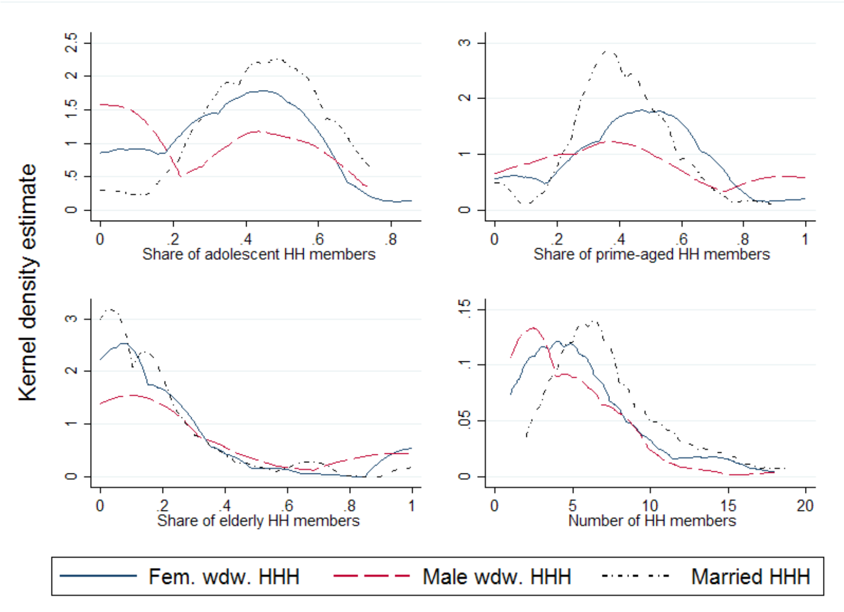
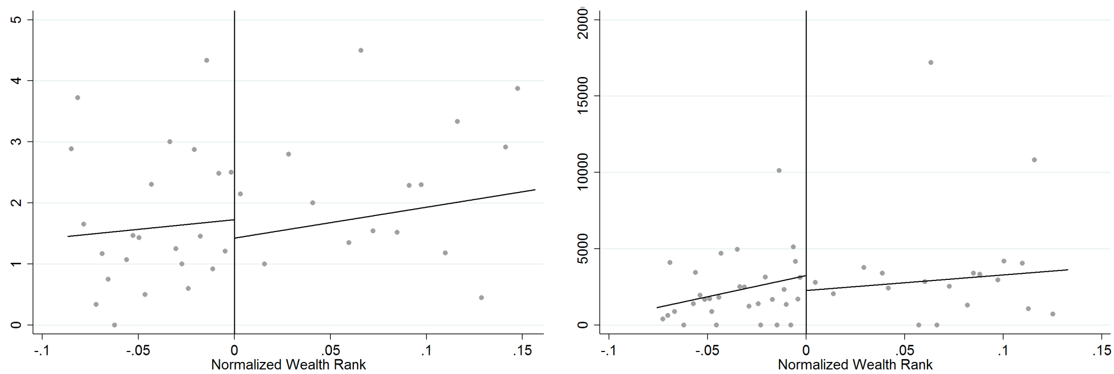


Figure 8: Household demographics by sex and marital status of household head, urban sector

Notes: Data are from the demographic census from 2009 and 2010. Only households within a symmetric bandwidth of 0.1 around the eligibility threshold are included.



(a) Total number of visits

(b) Total value of insurance claims

Figure 9: Testing for adverse selection, urban sector

Notes: We control for observable demographic household characteristics.

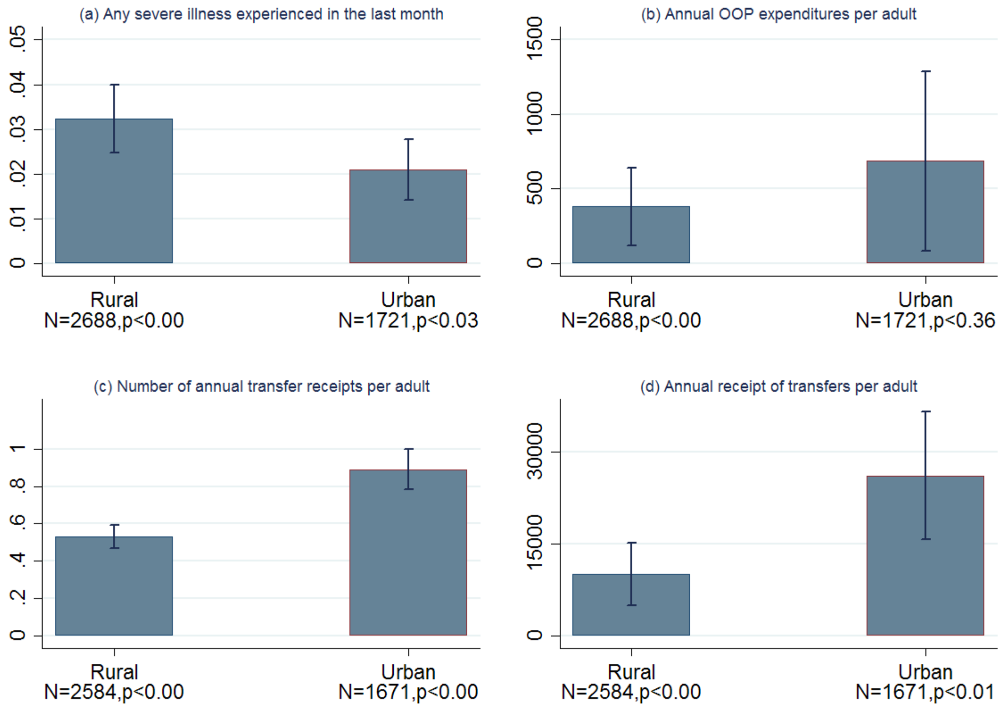


Figure 10: Burden of disease, health expenditures, and informal transfers (receipts), by sector

Notes: Survey sample contains adults from urban communities in 2006 to 2009 with a wealth ranks smaller than 0.2 in absolute value. Intervals depict the mean estimates' 95 percent confidence interval. P-values come from a linear regression with "Rural" as comparison group. OOP: out-of-pocket.

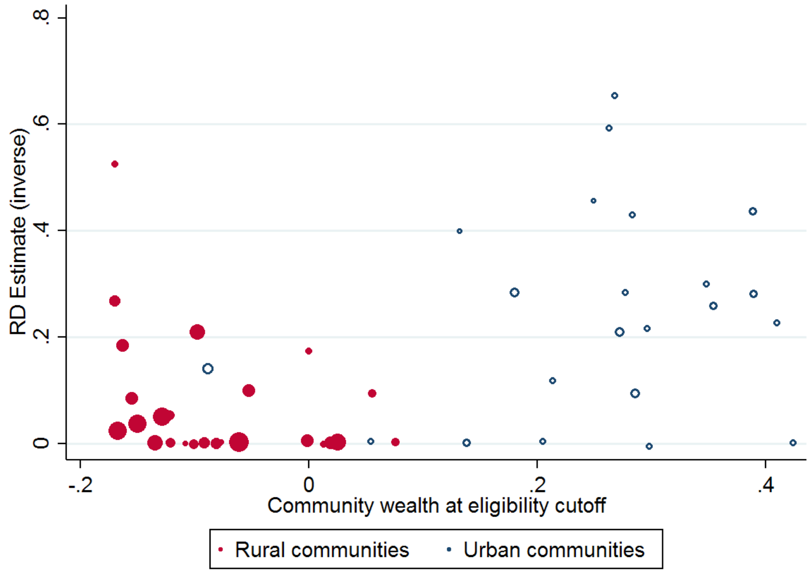


Figure 11: Regression discontinuity estimates by community

Notes: Each dot represents a community from the rural (solid) or urban (transparent) sector. The dot perimeter corresponds to community size. Communities are horizontally aligned with respect to community wealth around the cutoff, expressed in percentiles of the aggregate asset wealth distribution. For each community, the vertical scale gives the absolute value of the RD estimate for a community-wise local linear regression with a triangular kernel and an asymmetric manual bandwidth of 0.1 and 0.2, left and right of the eligibility cutoff, respectively.

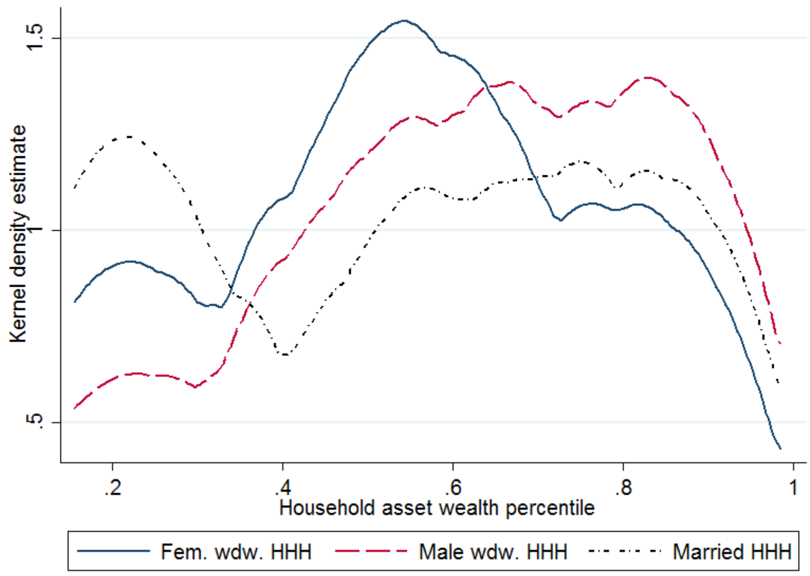


Figure 12: Wealth distribution by sex and marital status of household head, urban sector

Notes: Data are from the 2009 economic census. Only households within a symmetric bandwidth of 0.1 around the eligibility threshold are included. For the wealth index, see Notes to Figure 1.

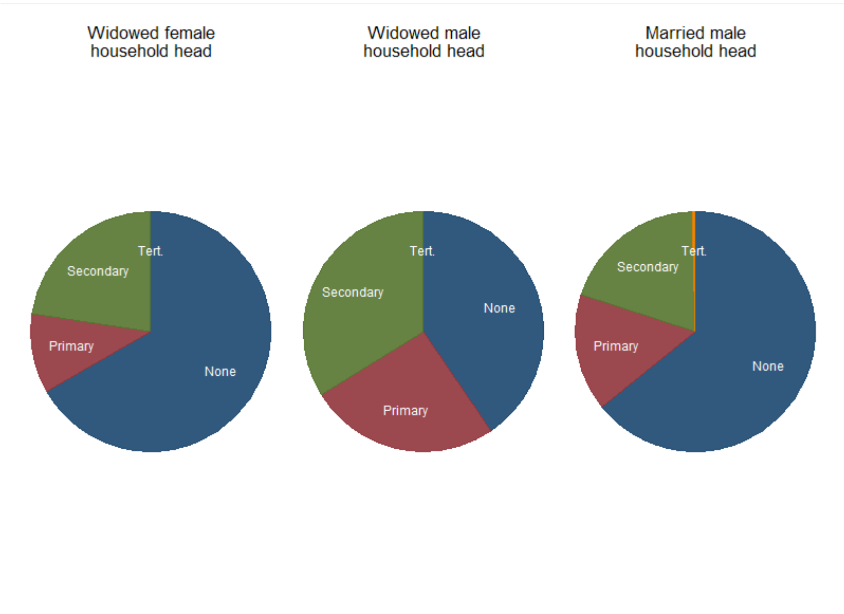


Figure 13: Education of household head by sex and marital status, urban sector

Notes: Data are from the demographic census from 2009 and 2010. Only households within a symmetric bandwidth of 0.1 around the eligibility threshold are included. The pie graph depicts the distribution of household head's maximum level of education.

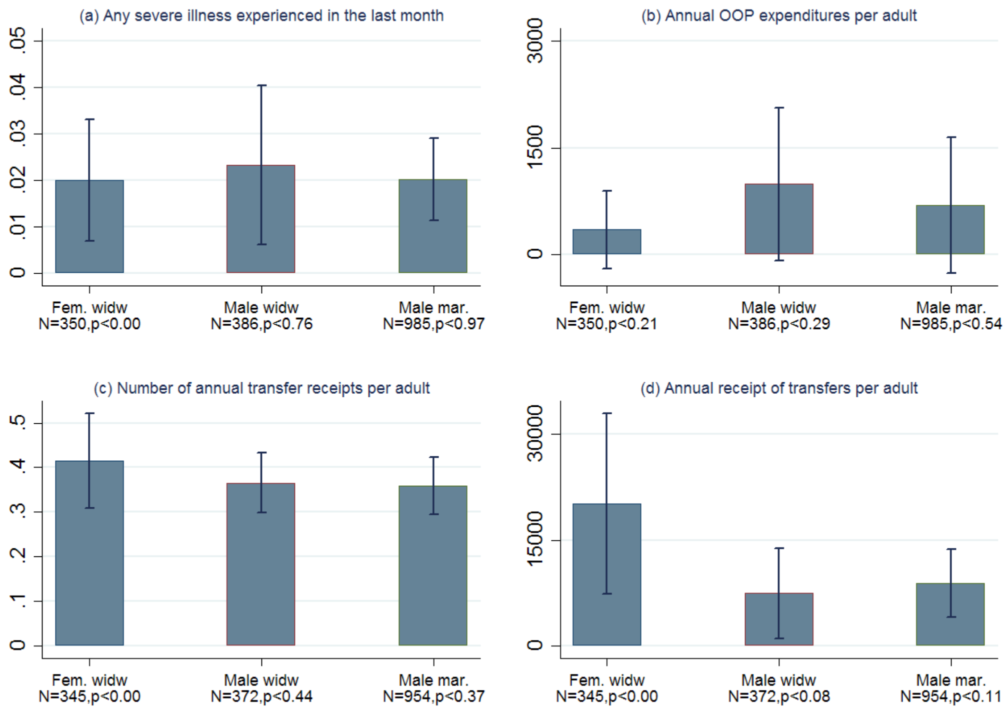


Figure 14: Burden of disease, health expenditures and informal transfers (receipts) by head of household type, urban sector

Notes: Survey sample contains adults from urban communities in 2006 to 2009 with a wealth ranks smaller than 0.2 in absolute value. Intervals depict the mean estimates' 95 percent confidence interval. P-values come from a linear regression with "Female-widowed" as comparison group. OOP: out-of-pocket.

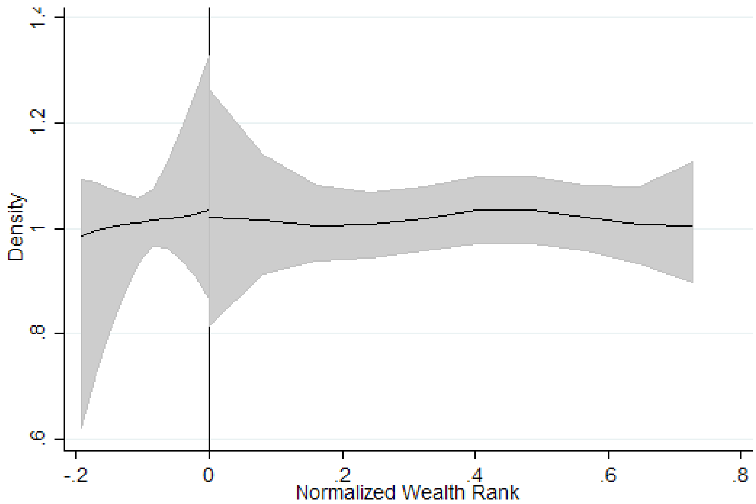
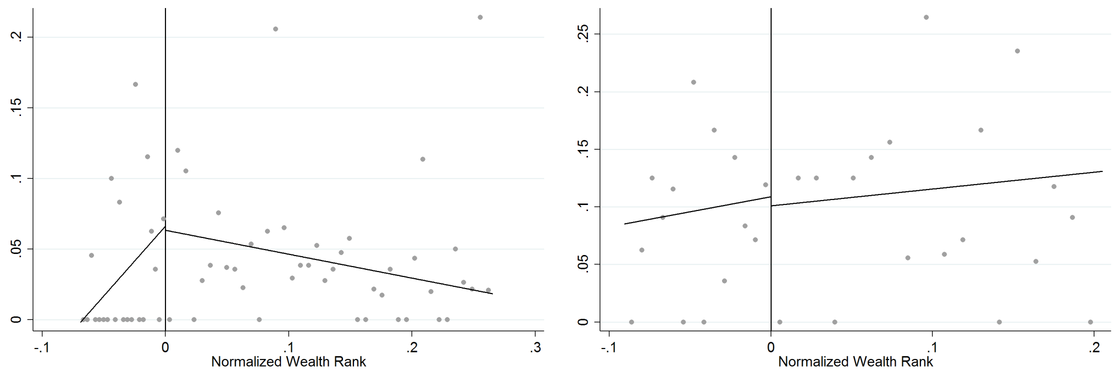


Figure 15: The distribution of the forcing variable, urban sector



(a) Rural

(b) Urban

Figure 16: Demand for health insurance, extensive margin, by sector: Placebo experiment

Table 1: Community-based targeting intervention

	Pooled	Rural	Urban
Ranked household per community	107	117	93
	(74)	(92)	(39)
Targeted households per community	21	23	18
	(15)	(19)	(7)
Targeted households per community (share)	0.20	0.20	0.20
	(0.01)	(0.01)	(0.01)
Targeted by all 3 informants	0.07	0.07	0.08
	(0.03)	(0.03)	(0.02)
Targeted by exactly 2 informants	0.11	0.11	0.12
	(0.31)	(0.31)	(0.32)
Targeted by exactly 1 informant	0.22	0.23	0.20
	(0.41)	(0.42)	(0.40)
Rank correlation between three informants	0.66	0.66	0.66
	(0.13)	(0.15)	(0.09)
Non-compliance rates			
Always-taker	0.03	0.04	0.02
	(0.18)	(0.19)	(0.15)
Never-taker	0.01	0.00	0.02
	(0.09)	(0.07)	(0.13)
Number of communities	50	28	22
Communities with always-takers	35	21	14
Communities with always-takers	2	0	2

Notes: Standard deviations in parentheses.

Table 2: Descriptive statistics

	Pooled		Rural		Urban	
	All obs. (1)	Cutoff obs (2)	All obs. (3)	Cutoff obs (4)	All obs. (5)	Cutoff obs (6)
Individual level						
Number of individuals	35,699	2,847	22,309	1,812	13,391	1,036
Enrollment rate	0.05	0.05	0.03	0.03	0.09	0.09
Total number of health care facility visits	2.3	1.8	2.4	1.9	2.2	1.7
Total value of insurance claims (CfA)	3,525	2,715	3,491	2,760	3,546	2,689
Literate individual	0.17	0.16	0.10	0.09	0.29	0.29
Household level						
Number of households	4,820	497	2,993	310	1,827	187
Share of targeted households	0.20	0.58	0.20	0.58	0.21	0.58
Normalized wealth rank	0.32	0.00	0.32	0.00	0.31	-0.00
Enrollment rate	0.10	0.09	0.06	0.05	0.15	0.16
Household size	7.50	5.80	7.53	5.89	7.44	5.64
Any educated household member	0.20	0.20	0.12	0.12	0.32	0.32
Non-agric. employed head of household	0.30	0.26	0.16	0.14	0.54	0.47
Share of female household members	0.49	0.49	0.49	0.46	0.48	0.53
Share of household members by age group						
Child (age $\leq$ 16)	0.45	0.42	0.48	0.45	0.41	0.37
Prime-aged (16 $<$ age $\leq$ 55)	0.40	0.40	0.38	0.39	0.44	0.42
Elderly (age $>$ 55)	0.15	0.18	0.14	0.16	0.16	0.21
Household head						
Widowed	0.21	0.30	0.15	0.20	0.31	0.46
Widowed male	0.10	0.13	0.08	0.11	0.14	0.17
Widowed female	0.12	0.16	0.08	0.09	0.18	0.28
Elderly	0.41	0.45	0.39	0.39	0.45	0.54
Elderly male	0.34	0.36	0.35	0.36	0.33	0.36
Elderly female	0.07	0.09	0.04	0.03	0.12	0.18
Prime-aged	0.59	0.55	0.62	0.61	0.56	0.46
Prime-aged male	0.54	0.48	0.58	0.55	0.49	0.36
Prime-aged female	0.05	0.08	0.04	0.06	0.07	0.10
Number of communities	50	50	28	28	22	22

Notes: Sample means for 2009 and 2010. Cutoff obs: Only observations with a normalized wealth rank smaller than 0.05 in absolute value.

Table 3: Subsidization and insurance demand

Dependent variable:	**Any household member insured in 2009 or 2010**							**Household size**
	Extensive Margin			Population			Intensive Margin	
	Pooled	Rural	Urban	Pooled	Rural	Urban	Urban	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD_Estimate	-0.106**	-0.024	-0.252***	-0.090**	-0.044	-0.174**	-0.020	0.326
	(0.043)	(0.033)	(0.090)	(0.038)	(0.032)	(0.084)	(0.136)	(2.039)
Outcome mean†	0.062	0.035	0.101	0.030	0.018	0.056	0.428	9.525
Bandwidth left	0.055	0.073	0.055	0.056	0.084	0.047	0.069	0.076
Bandwidth right	0.259	0.215	0.169	0.264	0.203	0.214	0.163	0.154
Unit of observation	HH	HH	HH	IND	IND	IND	IND	HH
Estimation sample	all HHs	all HHs	all HHs	all INDs	all INDs	all INDs	all INDs in ins HHs	ins HHs
Observations (left)	576	466	219	3184	2829	999	286	66
Observations (right)	2510	1310	612	17588	8119	5476	572	59
Number of communities	50	28	22	50	28	22	22	22

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors (clustered at the household) in parentheses. †Mean is calculated for the subsample of observations located above the cutoff and below the right-hand boundary of the bandwidth. all HHs: all households, all INDs: all individuals, ins HHs: all households with at least one insured household member, all INDs in ins HHs: all individuals from households with at least one insured household member.

Table 4: Insurance demand among subsidized households

Dependent variable:	**Any household member insured in 2009 or 2010**				
	All households		Urban household subgroups by household head characteristics		
	Rural	Urban	Widowed	Elderly	Prime-aged
	(1)	(2)	(3)	(4)	(5)
RD_Estimate	0.011	-0.272	-0.337*	-0.225	-0.292**
	(0.084)	(0.169)	(0.195)	(0.167)	(0.129)
Outcome mean†	0.044	0.132	0.143	0.167	0.159
Bandwidth left	0.073	0.055	0.055	0.064	0.095
Bandwidth right	0.215	0.169	0.210	0.260	0.172
Observations (left)	391	122	88	136	169
Observations (right)	135	38	32	28	23
Number of communities	17	12	12	9	11

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors (clustered at the household) in parentheses. †Mean is calculated for the subsample of observations located above the cutoff and below the right-hand boundary of the bandwidth.

Table 5: Subsidization and insurance demand by household head characteristics, urban sector

	Married household head	Widowed household head		Elderly household head		Prime-aged household head	
		Male	Female††	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RD_Estimate	-0.180*	-0.619***	-0.201	-0.405***	-0.190	-0.164**	-0.117
	(0.096)	(0.219)	(0.175)	(0.146)	(0.198)	(0.075)	(0.181)
Outcome mean†	0.100	0.114	0.118	0.123	0.134	0.081	0.085
Bandwidth left	0.087	0.060	0.051	0.070	0.057	0.082	0.109
Bandwidth right	0.222	0.108	0.305	0.242	0.272	0.103	0.241
Observations (left)	161	53	61	94	46	117	38
Observations (right)	518	70	204	301	112	161	71

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (clustered at the household) in parentheses. Dependent variable: Any household member insured in 2009 or 2010. †Mean is calculated for the subsample of observations located above the cutoff and below the right-hand boundary of the bandwidth. ††Except for two households, female household heads are widowed.

Table 6: Subsidization and individual enrollment by demographic characteristics, urban sector

	Child		Prime-aged		Elderly	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
RD_Estimate	-0.165	0.009	-0.147	-0.118	-0.465***	-0.443***
	(0.111)	(0.057)	(0.097)	(0.083)	(0.135)	(0.155)
Outcome mean†	0.047	0.055	0.053	0.050	0.055	0.069
Bandwidth left	0.059	0.052	0.048	0.055	0.048	0.058
Bandwidth right	0.311	0.212	0.308	0.210	0.189	0.298
Observations (left)	250	245	221	257	91	79
Observations (right)	1820	1266	1730	1169	291	389

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (clustered at the household) in parentheses. †Mean is calculated for the subsample of observations located above the cutoff and below the right-hand boundary of the bandwidth.

Table 7: Testing for adverse selection, urban sector

	Health care facility visits		Insurance claims	
	(1)	(2)	(3)	(4)
RD_Estimate	-0.020	0.012	-547.229	-51.802
	(0.726)	(0.769)	(1418.648)	(1472.494)
Outcome mean†	1.788	1.788	3203.407	3203.407
Bandwidth left	0.089	0.088	0.097	0.098
Bandwidth right	0.121	0.123	0.119	0.119
Controls††	No	Yes	No	Yes
Observations (left)	204	189	208	206
Observations (right)	226	189	226	189

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (clustered at the household) in parentheses. The estimation samples contains all insured individuals from 22 urban communities in 2009 and 2010. †Mean is calculated for the subsample of observations located above the cutoff and below the right-hand boundary of the bandwidth. ††Control dummy variables: female, prime-aged, elderly, extended family member

Table 8: Insurance demand in rural and urban sectors: the role of structural differences

	Any household member insured in 2009 or 2010			
	(1)	(2)	(3)	(4)
RD_Estimate	-0.179**	-0.276**	-0.279**	-0.176***
	(0.075)	(0.113)	(0.136)	(0.057)
Rural	-0.154**	-0.173***	-0.201***	-0.214***
	(0.073)	(0.044)	(0.048)	(0.045)
Rural*Subsidy eligibility	0.125	0.111**	0.145***	0.139***
	(0.080)	(0.048)	(0.051)	(0.048)
Wealth	0.104			
	(0.197)			
Wealth*Subsidy eligibility	0.001			
	(0.215)			
Household size		-0.029		
		(0.020)		
HH-size*Subsidy eligibility		0.024		
		(0.022)		
Number of literate HH members			-0.016	
			(0.029)	
Literacy*Subsidy eligibility			0.027	
			(0.031)	
Distance to next CSPS (km)				0.006
				(0.004)
Distance*Subsidy eligibility				-0.003
				(0.005)
Observations (left)	730	730	730	730
Observations (right)	2140	2140	2140	2140
Number of communities	50	50	50	50

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (clustered at the household) in parentheses. The estimation sample contains observations from 22 urban and 28 rural communities. Regression discontinuity design specification is a parametric local linear regression with triangular kernels and specified asymmetric bandwidths of -0.07 and 0.22 All additional covariates vary at the community level. Specifically, Wealth, HH-size, and Literacy are the estimated asset-index rank, household size, and number of literate household members for each community's household located at the top of the first wealth rank quintile.

Table 9: Internal validity test

	Any household member insured in 2007 or 2008				Share of	Any	Non-agric.
					female	educated	employed
				Household	household	household	head of
	Pooled	Rural	Urban	size	members	member	household
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RD_Estimate	-0.004	-0.003	-0.008	-0.077	0.039	-0.023	-0.047
	(0.028)	(0.030)	(0.060)	(0.545)	(0.063)	(0.061)	(0.056)
Outcome mean†	0.062	0.044	0.106	7.252	0.680	0.174	0.249
Bandwidth left	0.075	0.069	0.091	0.060	0.061	0.048	0.069
Bandwidth right	0.298	0.265	0.205	0.195	0.191	0.192	0.285
Observations (left)	694	412	280	301	303	264	375
Observations (right)	2690	1714	540	929	903	950	1415

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors (clustered at the household) in parentheses. †Mean is calculated for the subsample of observations located above the cutoff and below the right-hand boundary of the bandwidth.

Online Appendix

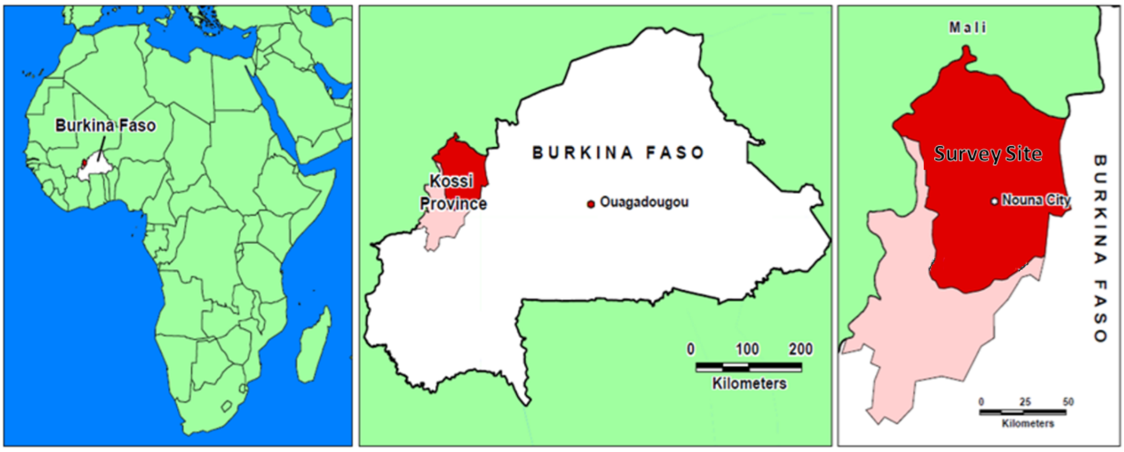


Figure A1: Location of the study site

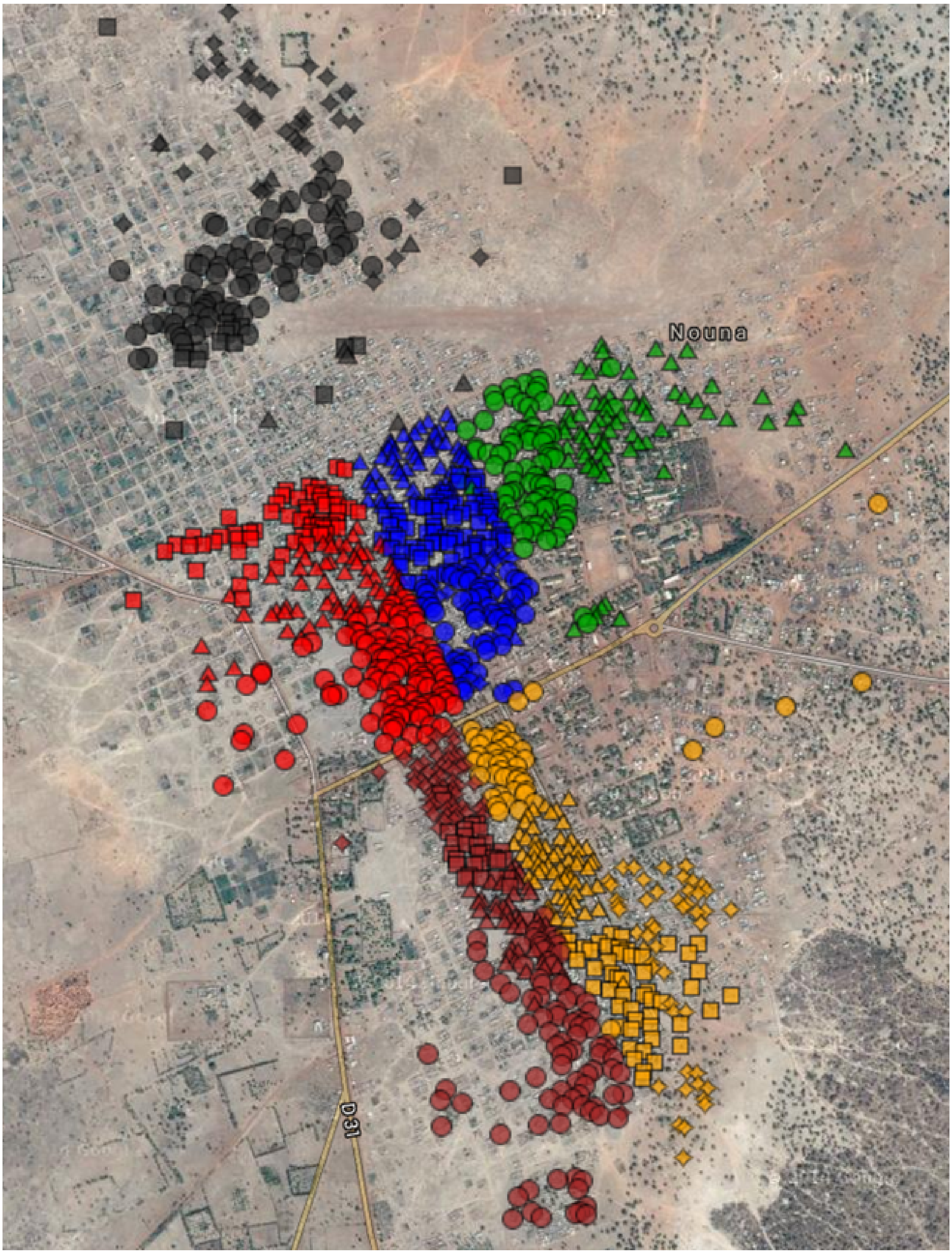


Figure A2: Urban communities of the study site