NBER WORKING PAPER SERIES

FINANCIAL RISK PROTECTION FROM SOCIAL HEALTH INSURANCE

Kayleigh Barnes
Arnab Mukherji
Patrick Mullen
Neeraj Sood

Working Paper 22620
http://www.nber.org/papers/w22620

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2016

This project was funded by the Health Results Innovation Trust at the World Bank. The findings, interpretations, and conclusions expressed in this paper do not necessarily reflect the views of the Executive Directors of The World Bank, the governments they represent, or the National Bureau of Economic Research. The World Bank does not guarantee the accuracy of the data included in this work.

Financial Risk Protection from Social Health Insurance
Kayleigh Barnes, Arnab Mukherji, Patrick Mullen, and Neeraj Sood
NBER Working Paper No. 22620
September 2016
JEL No. H0,H4,H51,I1,I13,I15,I3

ABSTRACT

This paper estimates the impact of social health insurance on financial risk reduction by utilizing data from a natural experiment created by the phased roll out of a social health insurance program for the poor in India. We estimate the impact of insurance on the distribution of out-of-pocket costs, frequency and amount of money borrowed for health reasons, and the likelihood of incurring catastrophic health expenditures. We use a stylized expected utility model to compute the welfare effects associated with changes due to insurance in the distribution of out-of-pocket costs. We adjust the standard model to account for the unique conditions of a developing country by incorporating consumption floors, informal borrowing, and selling of assets. These adjustments allow us to estimate the value of financial risk reduction from both consumption smoothing and asset protection channels. Our results show that social insurance reduces out-of-pocket costs with larger effects in the higher quantiles of the out-of-pocket cost distribution. In addition, we find a reduction in the frequency and amount of money borrowed for health reasons. Finally, we find that the value of financial risk reduction outweighs the total per household cost of the social insurance program by two to five times.

Kayleigh Barnes
Schaeffer Center for Health Policy
and Economics
635 Downey Way
Verna and Peter Dauterive Hall (VPD)
Los Angeles, CA 90089-7273
kayleighb@nber.org

Arnab Mukherji
Center for Public Policy
IIM Bangalore
Bannerghatta Road, Bangalore
Karnataka, India 560076
arnabmukherji@hotmail.com

Patrick Mullen
World Bank
Washington, DC
pmullen@worldbank.org

Neeraj Sood
Schaeffer Center for Health Policy
and Economics
3335 S. Figueroa Street, Unit A
Los Angeles, CA 90089-7273
and NBER
nsood@healthpolicy.usc.edu

1. Introduction

Universal health coverage is an increasingly accepted international development goal. Several developing countries are expanding government-funded health insurance to contribute to this goal as it provides a way to spread financial risk across taxpayers. In theory, health insurance coverage can improve welfare through two channels: improvements in health and reductions in financial risk due to lower out of pocket expenses. Studies examining the effects of access to health insurance in developing countries on financial risk protection have overwhelmingly focused on its impact on either average out-of-pocket health expenditure or on the incidence of catastrophic health expenditure.[1] These studies often rely on nationally representative cross-sectional surveys and the findings from this literature are mixed. While many papers report a decline in out-of-pocket health expenses, this finding is not consistent across all countries and all programs (Saksena, Hsu, & Evans, 2014; Van Doorslaer et al., 2007; Xu et al., 2007). Acharya et al. (2012) provide a review, documenting studies that show a decline in out-of-pocket expenditures due to social health insurance, others that show a rise in out-of-pocket expenditures, and still others that found no impact on out-of-pocket expenditures (Acharya et al., 2012).

More recently, Miller et al. (2009) compared distributions of out-of-pocket payments associated with eligibility for insurance in Colombia and find a lower distribution for inpatient payments associated with insurance, with the largest differences concentrated at the right tail of the distribution. There was no difference in the outpatient payment distributions (Miller, Pinto, & Vera-Hernández, 2009). Similarly, Bernal et al. (2014) compare cost distributions across eligibility to access social insurance in Peru. However, they find that eligibility is associated with increased out-of-pocket payments at the higher end of the distribution (Bernal, Carpio, & Klein, 2014). Thus, the impact of social insurance across the distribution of out-of-pocket expenses is poorly understood in developing economies. Some studies have also examined the welfare impact of insurance due to consumption smoothing by combining estimates of change in out-of-pocket cost distributions due to insurance with a stylized expected utility model. For example, Finkelstein and McKnight (2008) study the impact of the introduction of Medicare in the United States in 1965 and find that the welfare gains from consumption smoothing covered between half and three quarters of the costs of the program (Finkelstein & McKnight, 2008). This

[1] Catastrophic health expenditure is conceptually defined as out-of-pocket spending greater than the household's capacity to pay; empirically, health expenditure can be defined as catastrophic if it is greater than 40% of the household's non-subsistence expenditure or greater than 10% of the household's total expenditure (Ranson, 2002; Xu et al., 2003).

method of quantifying changes in financial risk due to universal health insurance has also been applied to developing countries; Limwattananon et al. (2015) compare data from Thailand on households benefiting from improved social health insurance coverage with households experiencing no change due to pre-existing coverage (for civil servants). They conclude that the improvement in insurance coverage had significant value for eligible households (Limwattananon et al., 2015). Additionally, Barofsky (2011) uses experimental data from Seguro Popular, a health insurance scheme in Mexico, and finds that welfare gains due to consumption smoothing cover roughly a quarter of program costs (Barofsky, 2011).

In this paper, we contribute to the literature on measuring financial risk reduction due to social health insurance by estimating the distributional effects of access to health insurance on out-of-pocket spending for below poverty line households in Karnataka, India. We use the standard quantile regression estimator presented by Koenker and Basset (1978) to predict changes in out-of-pocket payments conditional on having made such payments. Next, we use the three step censored quantile regression estimator developed by Chernozukhov and Hong (2002) to model the unconditional distribution of spending. We find that social insurance lowers the distribution of health care costs with larger effects at the right tail of the distribution.

In our welfare analysis, we explicitly account for a number of features specific to developing countries. Households in developing countries rely on a wide range of risk-mitigating strategies to deal with health shocks in the absence of market mechanisms (such as formal insurance) to manage risk (Gertler & Gruber, 2002; Morduch, 1995). For example, households may self-insure and dis-save from their assets to smooth consumption (Rosenzweig & Wolpin, 1993). Alternatively, they may depend upon village networks (borrowing within the same village) or social networks (borrowing within caste groups). If informal insurance helps smooth consumption, this would suggest that the gain from social health insurance may be relatively small as it would crowd out existing informal insurance mechanisms. However, Chetty and Looney (2006) argue that observed small fluctuations in consumption in developing countries may in fact hide very high welfare costs as poor households struggle to meet the costs of shocks (Chetty & Looney, 2006). For example, very poor households may take severe measures, such as selling productive assets or borrowing from a moneylender, in order to avoid their consumption dropping below subsistence. The existing stylized models for valuing health insurance do not capture these possible mechanisms that may feature in developing countries.

We extend the stylized choice model used to measure financial risk by incorporating a number of features that may be specific to developing countries. We incorporate a consumption floor to account for limited ability to cut back on consumption below a subsistence level. We also explicitly account for informal insurance in the model and allow households to sell assets to self-insure against high health care costs. Thus, we are able to capture the impact of insurance on both consumption smoothing and asset protection. We use plausibly exogenous variation in insurance coverage by exploiting a geographic discontinuity in the eligibility of a government-funded health insurance scheme, the Vajpayee Arogyashree Scheme (VAS), that provided coverage for expenses related to catastrophic illness to poor households in Karnataka, India. We find that the value of financial risk protection from insurance outweighs the average per household social costs of the insurance program by two to five times.

The rest of the paper is organized as follows. In Section 2, we discuss details of the health sector focusing on social health insurance and the VAS program in the state of Karnataka. In Section 3, we describe the natural experiment and the out-of-pocket health expenditure distributions. In section 4, we discuss the two-part censored quantile regression model that we use to model the distribution of out-of-pocket costs. In Section 5, we present our extension of the standard stylized choice model to incorporate features of a developing economy and present estimates of the value of insurance. Section 6 concludes by juxtaposing the value of insurance due to financial risk reduction with the cost of the program as well as the value of insurance stemming from improvements in health.

2. Background: Social Health Insurance in Karnataka

World Bank indicators state that between 2011 and 2015, health expenditure in India represented 4% of gross domestic product (GDP) and public expenditure on health was about 1.3% of GDP. These numbers have been steady for many years; for example, between 2001 and 2005 total health expenditure in India was 3.8% of GDP and public expenditure on health was about 1.1% of GDP. Approximately 70% of health care in India is procured through out-of-pocket purchases rather than through pooled financing mechanisms, such as formal health insurance (public or private) or, more importantly in India, the government funded health system. In the state of Karnataka, where VAS was rolled out in 2010, 73% of all hospitalizations in 2014 were reported to be in private institutions. This proportion was 82% among the urban population. (Government of India, 2015) A 2011-12 survey found that among the rural population in Karnataka, average medical expenses were 7.8% of total consumption expenditures, while among the urban population this proportion was 4.5% (Government of India, 2013a). This suggests that many households in Karnataka (and in India more generally) face large expenses in financing health care. Shahrawat and Rao (2012) use data from 2004 and find that about 5.8% of rural households and 3.21% of urban households faced catastrophic health expenditures (defined as out-of-pocket payments for health care that exceeded 40% of their total non-food consumption) (Shahrawat & Rao, 2012).

Although private health insurance coverage is growing among better-off households, the poor in India have little or no access to such formal market-based mechanisms to pool risk, so that households rely on individual and community-specific risk management strategies. Prior research shows that, among the rural population in India, 40% of out-of-pocket health expenditures were met by borrowing: 13% from contributions from social networks and 5% from sale of household assets (Shahrawat & Rao, 2012). Morduch and Rutherford (2003) review a number of empirical papers to show that such mechanisms rarely provide complete coverage (Morduch & Rutherford, 2003). These gaps in informal insurance not only retard income growth possibilities but may lead to poverty traps (Zimmerman & Carter, 2003). Estimates of the extent to which health shocks lead to poverty are difficult when the only reliable data is consumption expenditure, as is the case in India. A counter-intuitive implication of risk coping behaviors is that they would inflate consumption expenditure, and so, push households above the poverty line, reducing the measured incidence of poverty. Using data from India, Flores et al. (2008) develop a coping-adjusted health expenditure to total consumption ratio to show that ignoring out-of-pocket healthcare costs leads to an underestimate of poverty by 7-8% among households that face a hospitalization. They estimate 80% of this is due to risk mitigating behavior by households reflecting that household level adjustment is a commonly used response in developing countries (Flores, Krishnakumar, O'Donnell, & Van Doorslaer, 2008).

With the main policy objective of providing protection for the poor against health care expenditures, the central and several state governments in India have put in place a number of social health insurance schemes covering inpatient hospital care (La Forgia & Nagpal, 2012). Some evidence suggests that these programs have reduced out-of-pocket costs and borrowing to finance health care expenditures (Aggarwal, 2010; Rao et al., 2014). The program we study, VAS, was launched by the state government of Karnataka in 2010 in order to cover tertiary hospital services for households holding below poverty line, or BPL, cards. At that time there were limited alternative schemes that could be used to access catastrophic care in Karnataka. Yeshaswini, a cooperative based health insurance scheme, and Rastriya Swasth Bima Yojana (RSBY), were such programs implemented in Karnataka but the former had limited coverage of the poor while the latter did not cover tertiary care.

VAS reimburses hospitals based on a predefined price schedule for specific care packages covering more than 450 tertiary care services in seven disease areas including cardiology, oncology, neurology, nephrology, neonatology, burn care, and trauma care. Under VAS, hospitals need to meet infrastructure requirements (such as having an intensive care unit) and staff requirements (such as having specialists on staff) to be eligible to provide services to VAS beneficiaries (La Forgia & Nagpal, 2012). These empaneled hospitals can be either public or private, and at the time of our study, most services were provided by private hospitals. VAS beneficiaries are poor and most live in rural areas. Residents who possess a BPL card issued by the state government are automatically enrolled in VAS and beneficiaries pay no premiums or co-payments. Because most hospitals are located in urban centers in southern Karnataka while beneficiaries are located in villages as far as several hundred miles away, empaneled hospitals are required to organize health camps in rural areas to screen patients for tertiary care and subsequently transport them to hospitals. Hospitals sign an agreement to conduct these health camps during the empanelment process and receive a fixed payment per health camp conducted. Most rural patients receiving care through VAS in 2012 were identified through these health camps. VAS was originally rolled out in 2010 in northern Karnataka and expanded to the south only at the end of 2012. The state of Karnataka is divided into four administrative divisions – Bangalore and Mysore divisions in the south and Gulbarga and Belgaum divisions in the north. At the time of roll-out in 2010, the scheme was initiated in the districts in northern part of the state and later expanded to the south. These administrative divisions have been in place since the creation of the state in 1973 and the two divisions in the north include districts with the lowest human development indicators (Government of Karnataka, 2002). Thus, access to VAS required possession of a BPL card and residency in any of the districts in the two administrative divisions in north Karnataka. This creates a geographic discontinuity in access to the VAS at the border of the two administrative divisions in the north with the two administrative divisions in the south of Karnataka. This staggered roll-out created a natural experiment at the north-south boundary that Sood et al. (2014) exploit to compare a population that had access to the scheme with an equivalent population just south of the eligibility border that did not have access to the scheme (Sood et al., 2014). Access to social health insurance was associated with significantly lower mortality rate for conditions covered by VAS. Further, they reported lower out-of-pocket medical expenses for hospitalizations in tertiary care hospitals related to covered conditions.

3. Data

We surveyed households in 300 villages just north of the eligibility border and 272 villages just south side of the eligibility border (see Figure 1). The household survey asked respondents, usually the head of household, about details on out-of-pocket health expenditures relating to all hospital admissions and other details about household finances and demographic characteristics. In addition to the household survey, we also conducted a survey of one community health worker (known as an Asha) in each village to collect information on village level demographics, socioeconomic characteristics, and health behaviors. The sample of villages on the south side was chosen to be representative of the populations of Shimoga, Davangere, and Chitradurga, which are the northern-most districts of the southern administrative region of Karnataka. Villages from the south side are matched with a sample of villages (with replacement) from the VAS-eligible districts of Uttara Kannada, Haveri, and Bellary, on the basis of variables from the 2001 Census. A propensity score matching algorithm was implemented prior to collecting any data and was based on the census data. We use data on village population size, demographic structure, sex ratio for children under age 6, scheduled caste and scheduled tribe, levels of female literacy and population employed, to perform a nearest neighbor matching algorithm to match villages on the north and the south of the VAS coverage border. Figure 2 presents histograms of the estimated propensity score for villages covered by the program and those without the program indicating substantial overlap and, thus, comparability.

The top panel of Table 1 presents summary statistics of our key covariates after nearest neighbor matching on propensity scores and shows that there are no significant differences between villages with and without insurance. Further, when we compare these villages on other dimensions not used in the propensity score model we find few statistically observable differences between the groups. For example, the lower panels of Table 1 use data from our surveys with community health workers to show that these villages are comparable on multiple indicators, such as within village (un)healthy behaviors, mortality levels, population wide, and for females, which were not available in our propensity score model. One potentially important difference between our samples is bank access within a village. We find that our sample from the south is more likely to have access than our sample in the north. While this could be due to random chance, we control for differential access to banks in all our subsequent estimations.

We first listed all households in the study villages and find that 52% of households in the villages we sampled possessed below-poverty-line (BPL) cards issued by the state government, which make them eligible for subsidized food and other social benefits (including VAS benefits in the treatment villages). This proportion is consistent with a 2005-06 household survey that found that 47% of households in Karnataka had BPL cards (Ram, Mohanty, & Ram, 2009). We surveyed 6,964 households with BPL cards from the treatment and control villages and asked questions about out-of-pocket costs for medical care. Households with a hospitalization were over-sampled and survey weights were computed to correct for oversampling. Out-of-pocket costs are measured as the total expenditure associated with self-reported inpatient hospital treatment that includes hospital charges, medicines, and diagnostics. Table 2 presents summary statistics from our data. In our sample of 6,964 observations, 84% of the sample reports no medical costs related to hospital care. Of the households that do report expenses, the mean expense is Rs. 3,555, which is about 7.2% of their mean net worth. However, this number varies substantially, having a standard deviation of Rs. 14,274 (about 30% of net worth), and the highest levels of expenses account for about two-thirds of the relevant households' net worth.

4. Empirical Model

Distribution of Out-of-Pocket Health Care Costs

Acharya et al.'s review notes that many of the studies of social health insurance lack credible exogenous variation in insurance coverage. Further, these studies tend to focus on mean effects or the reduction in the size of the population facing catastrophic costs, rather than focusing on the effects of insurance across the entire distribution of out-of-pocket medical costs (Acharya et al., 2012). In line with these previous studies, we present measures of reduction in catastrophic costs as well as changes in the incidence of borrowing money to finance health care costs as preliminary evidence of financial risk reduction from access to health insurance. Xu et al. (2003) defines the catastrophic health expenditure limit as 40% of the household's non-subsistence expenditure while Ranson (2002) defines catastrophic expenditure as greater than 10% of annual household income (Ranson, 2002; Xu et al., 2003). We use these definitions as the basis for our analysis of the change in catastrophic health costs but alter them to better suit our data. We define subsistence expenditure as a household's food expenditure and use total consumption expenditure in place of income. In addition, we also look at alternate thresholds for both definitions of catastrophic expenditure. We allow the catastrophic limit to vary between 40% to 80% of non-subsistence expenditure and 10% to 50% of total consumption expenditure.

Given our interest in the distributional impacts of VAS, ordinary least square models are insufficient to measure the change in out-of-pocket payments because they only explicitly model the conditional mean. Koenker and Basset (1978) provide a general framework to estimate a series of conditional quantile functions across the range of the outcome to estimate the impact of covariates at different quantiles of the outcome variable (Koenker & Bassett Jr, 1978). This approach has been used to study the impact of an expansion in health insurance on out-of-pocket costs (Engelhardt & Gruber, 2011; Finkelstein & McKnight, 2008). One aspect of the out-of-pocket spending pattern that remains unexplored in these papers is the presence of excess zeros and skewed nature of health cost data. Beginning with Duan et al. (1983), the presence of excess zeros and over-dispersion in health cost data is widely studied and two-part hurdle models have been a standard way to model the conditional mean out-of-pocket payments (Duan, Manning, Morris, & Newhouse, 1983). Powell extended the framework developed by Koenker and Basset (1978) to a censored quantile regression that accounts explicitly for a large share of zeros, however it is computationally difficult (Powell, 1986). Chernozhukov and Hong (2002) suggest a three step estimator for censored quantile regression under the assumption that the underlying cost distribution is conditionally independent of the point of censoring (Chernozhukov & Hong, 2002). The procedure uses a probability model in the first stage to select a subset of households with a certain likelihood of incurring health costs. A quantile regression model is run on this subset, producing an inefficient estimate of the parameters of interest. These estimates are then used to select a second, typically larger sample of households on which quantile regression is applied again and efficient estimates are obtained. Limwattananon et al. (2015) use this two-step process to estimate the distributional impacts of the rollout of health insurance coverage in Thailand by comparing how the distribution of out-of-pocket costs changed for those who were covered due to the expansion in insurance coverage with those who always had health insurance (Limwattananon et al., 2015). We use the same strategy to estimate the unconditional distribution of out-of-pocket payments by estimating the quantile function of access to VAS using:

$$Q_{OOP_i|VAS_i,\boldsymbol{x_i};0}(\tau) = max(\beta_{0\tau} + \beta_{1\tau}VAS_i + \boldsymbol{x_i\beta_\tau}, 0);\ \tau = 1\ to\ 99$$

where OOP_imeasures the out-of-pocket health costs for household i, VAS_i is a binary indicator of access to the health insurance scheme, $\boldsymbol{x_i}$ is a set of control variables at the household level, 0 is the point of censoring which represents zero cost in our case and τ indicates the quantile at which the conditional quantile function is estimated. The parameter of interest here is $\beta_{1\tau}$ that measures the impact of access to VAS on out-of-pocket health costs at the τ^{th} quantile. Here, identification of $\beta_{1\tau}$is dependent on the variation in VAS being determined by the geographic discontinuity in its expansion. We use these estimates to construct out-of-pocket cost distributions associated with and without access to VAS. In addition to using the model presented by Chernozhukov and Hong (2002), we model the distribution of OOP conditional on having health costs using the standard quantile regression estimator presented in Koenker and Basset (1978). We drop all zeros from our data and estimate the conditional quantile function of access to VAS using:

$$Q_{OOP_i|VAS_i,\boldsymbol{x_i}}(\tau) = \delta_{0\tau} + \delta_{1\tau}VAS_i + \boldsymbol{x_i\delta_\tau};\ \tau = 1\ to\ 99$$

Again, we are interested in gaining inference on $\delta_{1\tau}$. All variables and parameters are of the same form as the censored quantile regression. We use parameter estimates from both regression models to predict counterfactual distributions for each household. Out-of-pocket payment distributions are then obtained by averaging counterfactual distributions within each quantile.

Stylized Utility Model

Changes in the distribution of out-of-pocket costs imply a gain in welfare for risk-averse households; in this section we extend the standard model to quantify such welfare gains. The standard CRRA utility model that has been used in prior work quantifies the welfare gains from insurance as the change in the money value that a household would pay to avoid the uncertainty of health shocks with and without insurance coverage (Engelhardt & Gruber, 2011; Feldstein & Gruber, 1995; Finkelstein & McKnight, 2008; Shigeoka, 2014). This way of valuing welfare gains has also been used in studying the expansion of social health insurance in developing countries such as in Thailand (Limwattananon et al., 2015) and in Mexico (Barofsky, 2011). However, these models do not consider risk-mitigating strategies that households resort to in order to finance medical costs (Gertler & Gruber, 2002). We incorporate informal borrowing, asset sales and consumption floors to the stylized utility model to account for risk mitigating strategies that are likely prevalent in developing countries.

Consider a household that earns an exogenously determined level of income (M) and wealth (W) where wealth measures the total value of various assets the household owns. This household derives utility from personal consumption C and household preferences are captured by a CRRA utility function: $U(C; M, W \alpha) = u(C)$, where utility is concave in consumption (i.e. $u'(.) > 0$; $u''(.) < 0$). The utility function takes the form:

$$u(C) = \begin{cases} \dfrac{1}{1-\gamma} C^{1-\gamma} & if\ \gamma \geq 0, \gamma \neq 1 \\ \ln(C) & if\ \gamma = 1 \end{cases}$$

Where γ is the relative risk aversion parameter of the household. The household faces a risk of poor health that requires expenditure. Similar to the rest of the literature on measuring welfare gains from expansion in health insurance, we model only the health care expenditures as a result of health shocks and ignore the implications of poor health on utility, health, and income. Thus, the household faces the risk of healthcare expenditure (OOP) shocks as captured by the probability distribution function $f(OOP)$ and is distributed over [0, ∞].

The first departure we make from the standard model is the introduction of a consumption floor, $\bar{C}$ that identifies a subsistence level consumption beyond which the household is unable to reduce their consumption, C, any further. We assume that healthcare costs, when experienced, are always large enough such that the household relies on its social network and borrows or sells assets to account for (1-x) of the total OOP and finances the remaining costs out of their income. Recent data show that, among the rural population in India, 40% of out-of-pocket health expenditures were met by borrowing: 13% from contributions from social networks and 5% from sale of household assets (Shahrawat & Rao, 2012). Thus for our baseline estimates, we assume that 60% of out of pocket costs are financed through informal insurance or borrowing and selling of assets. When the cost of health care is large enough that $M - x * OOP < \bar{C}$, the household finances all of the remaining health costs by borrowing more or selling additional household assets. When a household experiences a health shock, the household's wealth holding (W) adjusts through two possible mechanisms; a) the debt incurred due to borrowing from social networks and b) the additional sale of household assets. Thus, the household's choice problem can be written as:

$$\max_C U(C; \alpha) = u(C) \ \ni$$

$$C = \begin{cases} M - x * OOP, & C \geq \bar{C} \\ \bar{C}, & C < \bar{C} \end{cases}$$

$$W = \begin{cases} (1-x) * OOP, & C > \bar{C} \\ (1-x) * OOP + \bar{C} - (M - OOP), & C \leq \bar{C} \end{cases}$$

$$OOP \sim f(OOP)$$

We can specify the household's expected utility as:

$$EU_i = \int U(C_i) f(OOP_i) dOOP_i$$

Note that this expected utility can be calculated for any out-of-pocket payment distribution of interest. We calculate the expected utilities associated with the out-of-pocket payment distribution when a household has access to VAS and when a household does not have access to VAS. This, in turn, allows us to calculate the premium that the average risk-averse individual would be willing to pay to avoid facing the uncertainty. When households do not have access to VAS the money value of avoiding health shocks is captured by:

$$U(M - \pi^{NoVAS} | VAS = 0) = \int U(M - OOP) f(OOP) dOOP$$

Where π is the household's willingness to pay to avoid the costs associated with a health shock. Similarly, if the healthcare cost distribution associated with access to VAS is captured by $g(OOP)$ then the counterfactual money value that the household would pay to avoid health shocks is captured by:

$$U(M - \pi^{VAS} | VAS = 1) = \int U(M - OOP) g(OOP) dOOP$$

Thus, one can measure the financial risk reduction from the change in consumption smoothing opportunities that access to VAS allows as:

$$\Delta\pi = \pi^{VAS} - \pi^{NoVAS}$$

Apart from consumption smoothing, we know that levels of indebtedness and asset holding may also change as a result of access to VAS. To account for this, we define asset protection as the difference in the amount of out-of-pocket expenditure that had to be financed through informal insurance such as savings, selling of assets, or help from friends and family with and without VAS. Thus, the value of asset protection from having insurance is:

$$\Delta W = W^{NoVAS} - W^{VAS}$$

Thus, we see that that total value of insurance may be attributable to a component that measures the value of consumption smoothing and a component that measures the value from protecting the household's assets. Finally, note that the degree of risk aversion, γ, affects the concavity of the utility function and will play an important role in valuing the differences between the out-of-pocket payment distributions with and without health insurance. For low levels of income, a large enough health shock would hold the household consumption level at the threshold, $\bar{C}$. Consumption is then financed through borrowing and selling assets and the value of the insurance scheme in this situation comes from asset protection alone. As income rises the health insurance scheme goes beyond just protecting assets. As consumption increases above $\bar{C}$ (and expenditures fall below the level of out-of-pocket expenditure at which the household must sell assets) we expect to see that insurance provides a mix of asset protection as well as consumption smoothing. Finally, at high levels of income the curvature of the utility function flattens implying lower welfare gains from avoiding risk.

5. Results

Incidence of Borrowing and Catastrophic Costs

Table 3A shows that 24.2% of those who did not have access to VAS reported needing to borrow money to finance out-of-pocket medical costs. Among those who had access to the scheme, 20.7% reported the need to borrow money to finance out-of-pocket expenses, a statistically significant difference. Similarly we find that conditional on any borrowing at all, households with access to VAS on average borrowed Rs. 1,199 less than those who did not have access to the scheme.

We use multiple definitions of catastrophic health expenditure based on definitions used in Ranson (2002) and Xu et al. (2003) (Ranson, 2002; Xu et al., 2003). Findings for each definition are reported in Table 3B. We find weak evidence of reduction in the incidence catastrophic expenditures. We find reductions in incidence at every value of the catastrophic limit, however few of these reductions are statistically significant. Using Xu et al.'s (2003) definition, we find that access to VAS was associated with a 0.71% reduction in reaching the catastrophic level of expenditure at a 10% level of significance. Although the evidence for reduced incidence of catastrophic costs is weak, we find large reductions in the mean amount paid over the catastrophic limit. Our estimates of the reduction in the amount paid over the catastrophic limit range from Rs. 10,000 to Rs. 37,000, nearly all of which are statistically significant. These differences in the incidence of needing to borrow money or facing catastrophic health costs and in the amount borrowed or paid over the catastrophic limit suggest that financial risk protection is associated with VAS coverage.

Out-of-Pocket Cost Distribution

Key estimates of $\beta_{1\tau}$ and $\delta_{1\tau}$, representing the difference between the distributions with and without access to VAS at a given quantile, are presented in Table 4. We include values of these parameters for all 99 quantiles of our conditional quantile regression and our censored quantile regression in the appendix. Estimates of the change in the conditional distribution using the standard quantile regression model show a decrease in out-of-pocket expenditure associated with access to VAS at every quantile. Our parameter estimates are generally statistically significant except for at the highest quantiles of spending where the data is sparse. The median reduction in out-of-pocket payments conditional on having made such payments is Rs. 2,879 while the reduction in out-of-pocket expenditure at the 75th quantile is Rs. 4,485. In the unconditional distribution, households begin incurring out-of-pocket payments in the 79th quantile and our estimates show that at lower non-zero quantiles, VAS eligible households paid more than ineligible households, with a maximum difference in out-of-pocket payments of Rs. 1,257 in the 81st quantile. Spending by households ineligible for VAS overtakes spending by VAS–eligible households in the higher quantiles. The largest statistically significant difference in spending is Rs. 4,484 at the 94th quantile while the largest non-statistically significant difference in spending is Rs. 19,443 at the 99th quantile. Our estimates show little difference in out-of-pocket payments between VAS-eligible and VAS-ineligible households between the 86th and 90th quantiles. The discrepancy in out-of-pocket expenditure patterns at lower quantiles between the conditional and unconditional distributions is likely due to differences in utilization of hospital care. Wagstaff et al. (2009) postulate that unchanged or increased out-of-pocket payments associated with insurance may be due to increased health service utilization leading to additional fees being paid by households as well as additional uncovered services being provided (Wagstaff, Lindelow, Jun, Ling, & Juncheng, 2009). Access to VAS is associated with increased utilization of covered hospitalization but lower out-of-pocket costs conditional on use of covered services (Sood et al. 2014), which might explain the negative estimates in the conditional cost distribution but some positive estimates in the unconditional cost distribution. Despite this, both the conditional and unconditional distributions show greater financial risk protection at the highest levels of spending.

Figures 3A and 3B show these estimates graphically. Figure 3A plots the distribution of out-of-pocket payments conditional on having made any out-of-pocket payment for inpatient hospital care. We can see that the difference in out-of-pocket costs between VAS-eligible and VAS-ineligible households is negative for every quantile, indicating financial risk protection from access to VAS. These effects are increasingly large at higher quantiles. Figure 3B plots the unconditional distribution of out-of-pocket payments. We find similar patterns here as in Figure 3A, but now the first 79 quantiles are 0 for those both with and without access to VAS, indicating the large quantity of households that did not experience a health shock. For most quantiles, we see the same pattern as in the conditional distribution – lower levels of out-of-pocket payments for the VAS eligible group with reductions increasing at larger quantiles. However, unlike in our conditional distribution, we find slightly larger payments in the VAS group in the first non-zero quantiles. We provide the full distributions of out-of-pocket costs in the appendix. Conditional on having made any out-of-pocket payment for inpatient hospital care, the mean reduction in out-of-pocket costs across quantiles associated with VAS coverage is Rs. 5,203. When including the likelihood of not having made any out-of-pocket payment and applying Chernozhukov and Hong's (2002) approach, the mean reduction in out of pocket costs is Rs. 463.

Welfare Calculations

We implement the algorithm described in the methods section and calculate $\Delta\pi$ and ΔW for different levels of income and risk aversion parameters, which provides an estimate of the value of the change in the distribution of out-of-pocket payments from accessing VAS. A summary of our estimates can be found in Table 5. As described in our stylized choice model, we assume that households use coping mechanisms (informal insurance) to meet at least 60% of out-of-pocket health expenditures. If the remaining 40% of expenditure still exceeds subsistence consumption, households fund the rest of out-of-pocket costs with more borrowing and asset sales. Our analysis considered four levels of income, four values of risk aversion, and three consumption floors. Our subsistence consumption levels are defined as 20% of income, the poverty line, and the median food expenditure of households in our sample (Government of India, 2013b). Setting subsistence at 20% of income is consistent with the method used by Finkelstein and McKnight (2008) and using the median food expenditure is similar to Xu et al. (2003) (Finkelstein & McKnight, 2008; Xu et al., 2003). The lowest income levels are set at the level of food subsistence and the poverty line. The other two levels of income are set at the median and 75th quantile of the India Human Development Survey estimates of income for Karnataka (Desai, 2015).

In the risk neutral case (γ=0), the value of insurance, Rs. 463, is equal to the mean difference in out-of-pocket payments across all quantiles in the unconditional distribution. This finding is expected, as no extra value is placed on consumption spending in the risk neutral case, and serves to check whether our algorithm was implemented correctly. As we consider higher levels of risk aversion for the same level of income and consumption floor, the value of insurance generally increases. This is due to the extra value placed on consumption smoothing in more risk averse households. The exception is when income is at or below subsistence level consumption to begin with, so that no consumption smoothing occurs at any level of risk aversion. The value of asset protection remains fixed indicating the fixed adjustment in the stock of wealth that the household makes in financing health costs. Limwattananon et al. (2015) suggest that a risk aversion parameter of 3 is consistent with the average income of households in Thailand (Limwattananon et al., 2015). Using this parameter, we estimate the insurance value of the program to be between Rs. 463 and Rs. 1,075 per household. Chetty and Looney (2006) state that poor households are likely to be highly risk adverse, taking all possible options to keep consumption above subsistence level (Chetty & Looney, 2006). The BPL households in our sample, with a much lower average income than the sample studied in Limwatananon et al. (2015), may exhibit much higher risk aversion. Using higher relative risk aversion parameters of 4 and 5, we find that the total value of insurance is between Rs. 463 and Rs. 2,689.

As income increases within a given level of risk aversion and subsistence consumption level, the total value of the insurance rises then falls. At an income equal to or below the level of subsistence, we find that the consumption smoothing value of insurance is zero because even in the presence of health shocks there is no change in consumption and, thus, no consumption smoothing. For this case, the entire value of insurance comes from the savings incurred from the reduced likelihood of asset sales which is Rs. 463. As income levels rise above the consumption floor we see that households' value of insurance rises due to the consumption smoothing role of insurance. At the same time, the amount of asset sales or borrowing needed to finance the same health shock declines and stabilizes for high levels of incomes. As income levels rise to the 75th percentile of the income distribution we find that the aggregate value of insurance as well as the value of the consumption smoothing role of insurance declines. At high levels of income, health shocks are a smaller fraction of consumption expenditure and while these households still value the consumption smoothing effect, it is not valued as much as it is at lower levels of income.

Finkelstein and McKnight compare their estimate of the value of social health insurance for the elderly in the United States with the social cost of the program, defined as the deadweight loss resulting from raising the necessary government revenue plus the costs due to moral hazard effects of the insurance (Finkelstein & McKnight, 2008). Similar approaches are used to study Japan and Thailand (Limwattananon et al., 2015; Shigeoka, 2014). Based on data from a census of BPL households in the study villages presented in Sood et al. (2014) we estimate that VAS covered 3.19% of all hospitalizations in VAS eligible villages representing 0.47 hospitalizations per 100 BPL households. This reflects the fact that VAS covered tertiary care-related hospitalizations for only seven conditions. However, these tertiary care hospitalizations (such as bypass surgery) were much more expensive than hospitalizations not covered by the program. Data from Sood et al. 2014 show that households in VAS-ineligible villages paid on average Rs. 62,996 for hospitalizations for covered conditions in tertiary care facilities. Thus, hospitalizations covered by VAS were roughly 15 times more expensive than the average hospitalization. Similarly, administrative data from the year preceding our survey (2011-12) show that the average amount paid per hospitalization by VAS was Rs. 57,517, roughly matching the hospital costs reported in survey data. Multiplying the average amount paid by VAS with the rate of hospitalizations covered by VAS per household results in a government cost per household of Rs. 270. Prior studies assume a deadweight loss of roughly one third of total government expenditures, resulting in a social cost of Rs. 90 per eligible household. Sood et al. 2014 show that VAS increased utilization of covered hospitalizations by 20 to 40%; assuming a 30% increase in utilization of covered services results due to "moral hazard" results in an increased cost of Rs. 60. Thus the assumed deadweight plus moral hazard cost of the program is roughly Rs. 150 per eligible household. Applying what we consider to be reasonable parameters (risk aversion parameter of 4, consumption floor at food subsistence and income at the poverty line) results in an insurance value of the program of Rs. 679, (Table 6) roughly 4 times the possible deadweight cost of funding the program of Rs. 150 per household. Our lowest estimate for the total insurance value of the program, Rs. 463, similarly exceeds the social cost of the program. We believe that the insurance value of the program is much higher than the social cost of the program for several reasons. First, unlike other insurance programs, which cover most inpatient and outpatient care (such as Medicare), VAS covered only catastrophic health care expenses. This focus on rare but expensive hospitalizations increases the insurance value of the program and reduces the social costs of the program. Second, we believe VAS had important spillover effects on non-tertiary care that further reduced out-of-pocket costs of VAS beneficiaries. Sood and Wagner (2015) showed that VAS increased treatment-seeking behavior for symptoms that could lead to expensive hospitalizations if left undiagnosed and untreated. For example, they show that persons in VAS-eligible villages were much more likely to seek medical care for symptoms of cardiac disease such as chest pain. They also show that VAS beneficiaries had better post-operative outcomes such as lower rates of rehospitalizations and complications. These better post-operative outcomes could further reduce hospital costs. Finally, VAS paid hospitals prospectively and had a strict prior authorization process. Both these features could reduce care along the intensive and extensive margins. These spillover effects and unique features of VAS could explain why the government cost of providing tertiary care through the program was lower than the out of pocket cost reductions.

We also use back-of-the-envelope calculations to compare the financial risk protection value of the program to the value of the program generated through improvement in health (Nyman, 1999). Basu, Benavid, and Sood (2015) use data from VAS to estimate the disability adjusted life years (DALYs) averted due to better access to tertiary care for cardiac disease provided to VAS beneficiaries (Basu, Bendavid, & Sood, 2015). Basu, Benavid, and Sood (2015) find that access to VAS for cardiac care was associated with about 2,077 DALYs averted per million in the population. Cardiac disease has a high prevalence in India and we use DALYs averted from VAS for cardiac care as an approximation for the DALYs averted from access to VAS for all conditions. Over the past decade, World Bank estimates of per capita GDP in India have been about $1500. Consistent with the literature, we use three times the per capita GDP as an estimate of the value of a DALY and calculate that access to VAS was associated with $9.34 or Rs. 625 welfare gain per person due to improved health. This value is comparable in size to our estimates of the value of financial risk reduction and suggests that social insurance improves welfare through both improvements in health and improvements in financial well-being.

6. Discussion

The main policy objective of this social insurance program in Karnataka, India, was to contribute to financial protection of poor households affected by health conditions requiring costly tertiary hospital care. In terms of commonly used indicators for measuring financial protection, notably average out-of-pocket spending and catastrophic health care expenditure, our findings indicate that VAS achieved this objective. Among the entire sample (not conditioning on households having any health care expenditures), average out-of-pocket spending on inpatient care before the statewide rollout was Rs. 463 lower for BPL households eligible for VAS compared to ineligible BPL households. Among those who had made out-of-pocket payments for inpatient care, the mean difference was Rs. 5,203. As previously noted, the literature is mixed with regard to the financial protection effects of social health insurance in developing countries. Our results are consistent with several studies reviewed by Acharya et al. (2012) and studies of Medicare programs in the United States that indicated reduced out-of-pocket payments associated with insurance (Acharya et al., 2012; Engelhardt & Gruber, 2011; Finkelstein & McKnight, 2008). At the same time, our findings contrast with other studies reviewed by Acharya et al. (2012) as well as a recent study of Peru, which found unchanged or increased out-of-pocket spending associated with expansion of social health insurance (Acharya et al., 2012; Bernal et al., 2014). The higher out-of-pocket expenditures at higher levels of the distribution in Peru were explained by the possibility that individuals who reached maximum coverage paid for more services. However, this does not seem to be evident in the Karnataka case, where service packages were defined (by a committee including tertiary hospital directors) with the intention that they be comprehensive in terms of required services for given conditions and with rates reflecting input costs and market prices. These mixed results reflect the heterogeneity of the programs evaluated and the settings in which they were implemented.

A strength of our study is its quasi-experimental design, which relies on geographic discontinuity in health insurance coverage where households to the north of the administrative border within a state had access to government-provided insurance and households just south of the border were not eligible for government-provided insurance. We used a variety of data to show that eligible and ineligible households living on either side of this administrative boundary were otherwise similar. One potential limitation of our study is possible measurement error related to self-reported data on out-of-pocket payments. Misreporting and lack of data also limited our analysis of the welfare gains associated with access to insurance. Income and wealth data in developing countries can be unreliable and difficult to obtain, requiring our welfare analysis to be run for specific levels of income. Accurate income and wealth data would allow for more precise measurement of the welfare gains from access to VAS. However, our results are consistent with the only similar analysis applied to a developing country, Thailand, where the estimated financial protection value of an insurance program outweighs its efficiency cost (Limwattananon et al., 2015).

Our analysis highlights the importance of the consumption smoothing and asset protection effects of access to insurance, specifically in a developing country. The value of financial risk protection from VAS was much higher than the social cost of the program and comparable to the welfare gain from improved health. We believe that VAS provided better value for money than other insurance programs analyzed in the literature for several reasons. First, it focused on rare but expensive and potentially life saving hospitalizations. Second, it facilitated access to these hospitalizations by organizing health camps, not requiring any additional paperwork for enrollment in the scheme, and operating a "cashless" scheme where beneficiaries received comprehensive care at no out of pocket costs. Third, VAS paid hospitals prospectively for a bundle of services and instituted a robust pre-authorization process. These unique features of the program led to lower costs for the government and better access to life saving treatments for beneficiaries. More research is needed to identify innovations that improve the value of universal health insurance.

References:

Acharya, A., Vellakkal, S., Taylor, F., Masset, E., Satija, A., Burke, M., & Ebrahim, S. (2012). The impact of health insurance schemes for the informal sector in low-and middle-income countries: a systematic review. *The World Bank Research Observer*, lks009.

Aggarwal, A. (2010). Impact evaluation of India's 'Yeshasvini'community-based health insurance programme. *Health economics, 19*(S1), 5-35.

Anagol, S. (2009). Adverse Selection in Asset Markets: Theory and Evidence from the Indian Market for Cows Job Market Paper.

Barofsky, J. (2011). Estimating the impact of health insurance in developing nations: Evidence from Mexico's Seguro Popular. *Harvard School of Public Health, Cambridge, MA*.

Basu, S., Bendavid, E., & Sood, N. (2015). Health and Economic Implications of National Treatment Coverage for Cardiovascular Disease in India Cost-Effectiveness Analysis. *Circulation: Cardiovascular Quality and Outcomes, 8*(6), 541-551.

Berman, P., Ahuja, R., & Bhandari, L. (2010). The impoverishing effect of healthcare payments in India: new methodology and findings. *Economic and Political Weekly*, 65-71.

Bernal, N., Carpio, M. A., & Klein, T. J. (2014). The Effects of Access to Health Insurance for Informally Employed Individuals in Peru: Institute for the Study of Labor (IZA).

Chernozhukov, V., & Hong, H. (2002). Three-Step Censored Quantile Regression and Extramarital Affairs. *Journal of the American Statistical Association*, 872-882.

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

Desai, S., Reeve Vanneman and National Council of Applied Economic Research, New Delhi. (2015). *India Human Development Survey-II (IHDS-II), 2011-12 ICPSR36151-v2*.

Duan, N., Manning, W. G., Morris, C. N., & Newhouse, J. P. (1983). A comparison of alternative models for the demand for medical care. *Journal of business & economic statistics, 1*(2), 115-126.

Engelhardt, G. V., & Gruber, J. (2011). Does Medicare Part D Protect the Elderly from Financial Risk? *American Economic Journal: Economic Policy, 3*(4), 77-102.

Feldstein, M., & Gruber, J. (1995). A major risk approach to health insurance reform *Tax Policy and the Economy, Volume 9* (pp. 103-130): MIT Press.

Finkelstein, A., & McKnight, R. (2008). What did Medicare do? The initial impact of Medicare on mortality and out of pocket medical spending. *Journal of public economics, 92*(7), 1644-1668.

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

Gertler, P., & Gruber, J. (2002). Insuring Consumption Against Illness. *American Economic Review, 92*(1), 51-70.

Government of India. (2013a). *Key Indicators of Household Consumer Expenditure in India, NSS 68th Round (July 2011-June2012)*. New Delhi: National Sample Survey Office Retrieved from http://mospi.nic.in/Mospi_New/upload/Report_no558_rou68_30june14.pdf

Government of India. (2013b). *Press Note on Poverty Estimates, 2011-2012*. New Delhi: Retrieved from http://planningcommission.nic.in/news/pre_pov2307.pdf

Government of India. (2015). *Key Indicators of Social Consumption in India: health, NSS 71st Round (January-June 2014)*. New Delhi: National Sample Survey Office Retrieved from http://mospi.nic.in/Mospi_New/upload/nss_71st_ki_health_30june15.pdf

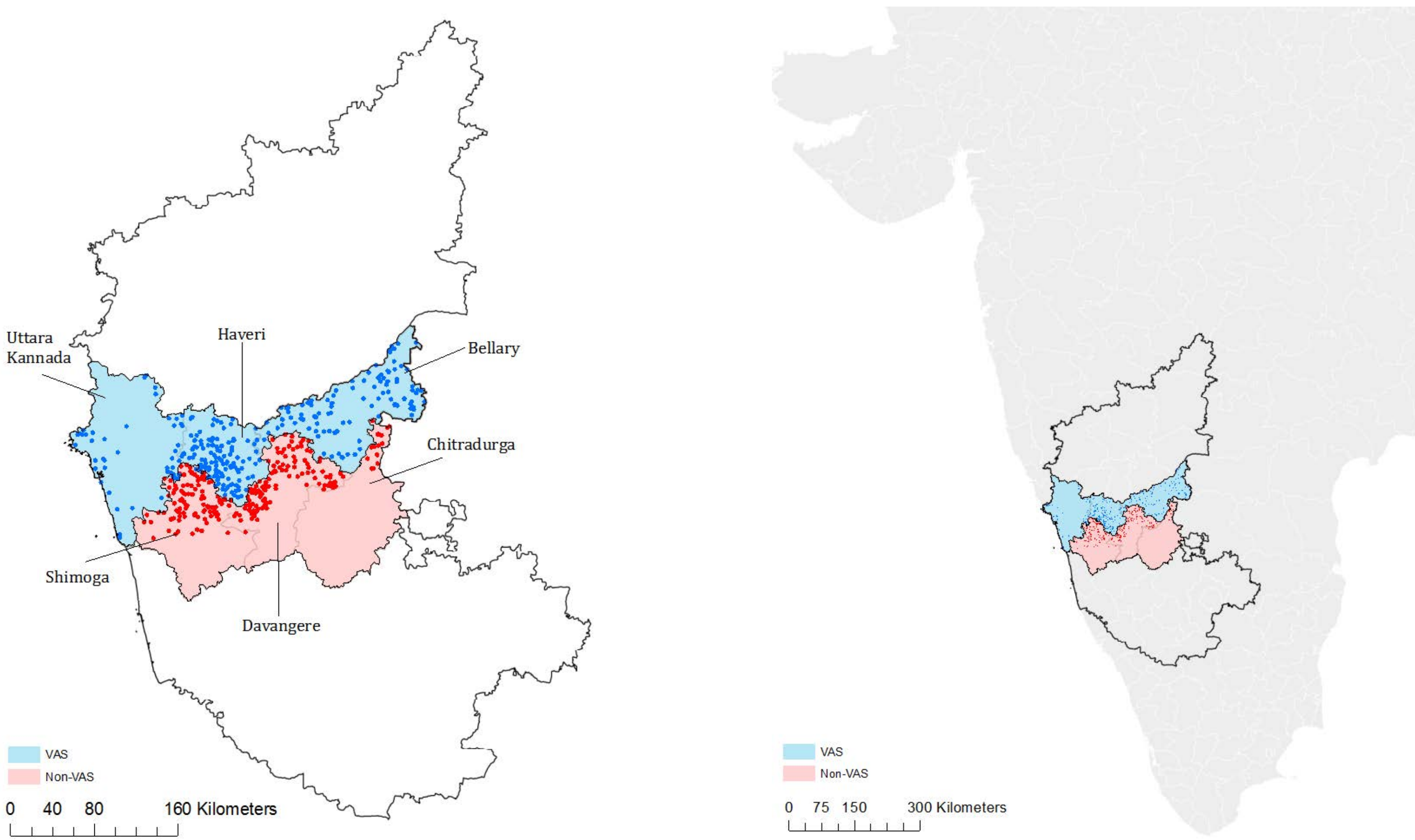
Government of Karnataka. (2002). *High Power Committee on Regional Imbalances Redressal*. Bangalore: Retrieved from http://planning.kar.nic.in/node/56.html

India Registrar General. (2011). Census of India, 2011. *India, Provisional Population Totals, Paper, 1*.
Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, 33-50.
La Forgia, G., & Nagpal, S. (2012). *Government-sponsored health insurance in India: Are you covered?* : World Bank Publications.
Limwattananon, S., Neelsen, S., O'Donnell, O., Prakongsai, P., Tangcharoensathien, V., van Doorslaer, E., & Vongmongkol, V. (2015). Universal coverage with supply-side reform: The impact on medical expenditure risk and utilization in Thailand. *Journal of public economics, 121*, 79-94.
Miller, G., Pinto, D. M., & Vera-Hernández, M. (2009). Risk protection, service use, and health outcomes under Colombia's health insurance program for the Poor: National Bureau of Economic Research.
Morduch, J. (1995). Income smoothing and consumption smoothing. *The journal of economic perspectives, 9*(3), 103-114.
Morduch, J., & Rutherford, S. (2003). Microfinance: analytical issues for India. *Background paper prepared for the World Bank*.
Nyman, J. A. (1999). The value of health insurance: the access motive. *Journal of health economics, 18*(2), 141-152.
Powell, J. L. (1986). Censored regression quantiles. *Journal of econometrics, 32*(1), 143-155.
Ram, F., Mohanty, S., & Ram, U. (2009). Understanding the distribution of BPL cards: All-India and selected states. *Economic and Political Weekly*, 66-71.
Ranson, M. K. (2002). Reduction of catastrophic health care expenditures by a community-based health insurance scheme in Gujarat, India: current experiences and challenges. *Bulletin of the World Health Organization, 80*(8), 613-621.
Rao, M., Katyal, A., Singh, P. V., Samarth, A., Bergkvist, S., Kancharla, M., . . . Renton, A. (2014). Changes in addressing inequalities in access to hospital care in Andhra Pradesh and Maharashtra states of India: a difference-in-differences study using repeated cross-sectional surveys. *BMJ open, 4*(6), e004471.
Rosenzweig, M. R., & Wolpin, K. I. (1993). Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India. *Journal of political economy*, 223-244.
Saksena, P., Hsu, J., & Evans, D. B. (2014). Financial risk protection and universal health coverage: evidence and measurement challenges. *PLoS Med, 11*(9), e1001701.
Shahrawat, R., & Rao, K. D. (2012). Insured yet vulnerable: out-of-pocket payments and India's poor. *Health Policy & Planning, 27*(3).
Shigeoka, H. (2014). The Effect of Patient Cost Sharing on Utilization, Health, and Risk Protection. *American Economic Review, 104*(7), 2152-2184.
Sood, N., Bendavid, E., Mukherji, A., Wagner, Z., Nagpal, S., & Mullen, P. (2014). Government health insurance for people below poverty line in India: quasi-experimental evaluation of insurance and health outcomes. *BMJ (Clinical research ed.), 349*, g5114.
Van Doorslaer, E., O'Donnell, O., Rannan-Eliya, R. P., Somanathan, A., Adhikari, S. R., Garg, C. C., . . . Ibragimova, S. (2007). Catastrophic payments for health care in Asia. *Health economics, 16*(11), 1159-1184.
Wagstaff, A., Lindelow, M., Jun, G., Ling, X., & Juncheng, Q. (2009). Extending health insurance to the rural population: An impact evaluation of China's new cooperative medical scheme. *Journal of health economics, 28*(1), 1-19.
Xu, K., Evans, D. B., Carrin, G., Aguilar-Rivera, A. M., Musgrove, P., & Evans, T. (2007). Protecting households from catastrophic health spending. *Health affairs, 26*(4), 972-983.

Xu, K., Evans, D. B., Kawabata, K., Zeramdini, R., Klavus, J., & Murray, C. J. (2003). Household catastrophic health expenditure: a multicountry analysis. *The lancet, 362*(9378), 111-117.

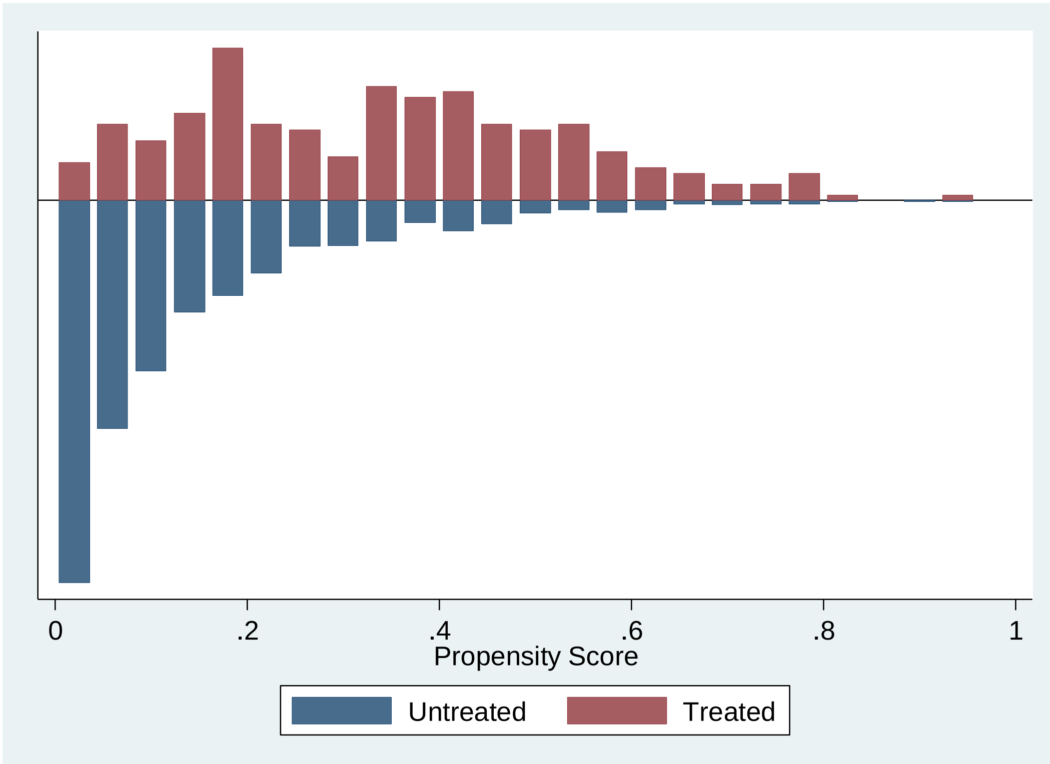
Zimmerman, F. J., & Carter, M. R. (2003). Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. *Journal of Development Economics, 71*(2), 233-260.

Figure 1: Map of Study Area



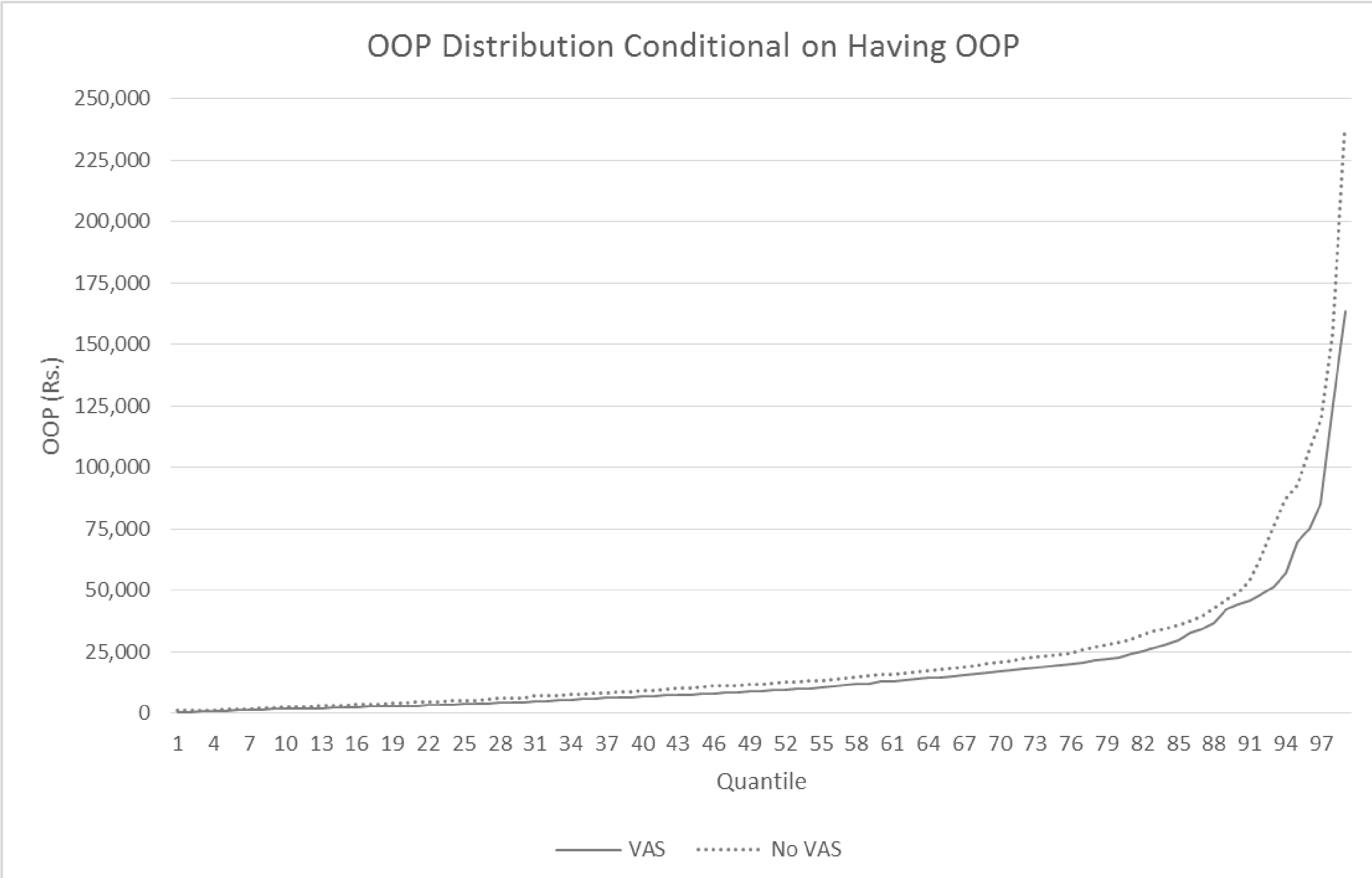
Notes: Dots represent sampled villages. The map on the left is the state of Karnataka and the map on the right is zoomed out to show the Southeastern regions of India.

Figure 2 Propensity Scores for villages with and without Health Insurance



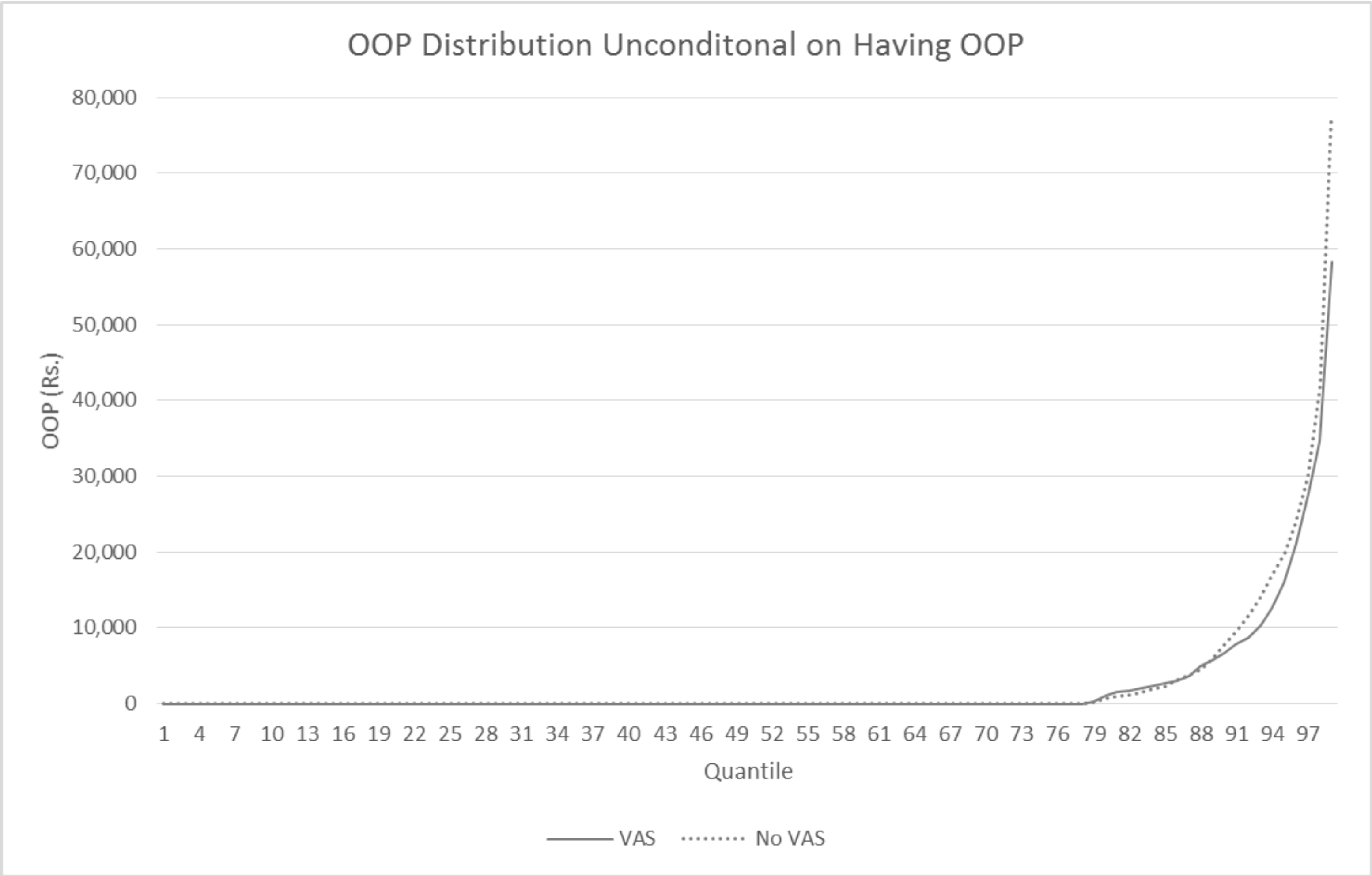
Note: Distribution of estimated propensity score for VAS (Treated) and non-VAS (Untreated) villages in our sample. The above diagram indicates we have extensive overlap in the range of propensity scores in both treated and untreated villages.

Figure 3A: Out of Pocket Cost Distribution conditional on having a health shock



Note: Graph was created using values predicted from parameter estimates obtained in a quantile regression run conditional on households experiencing health costs.

Figure 3B: Out of Pocket Cost Distribution unconditional on having a health shock



Note: Graph was created using values predicted from parameter estimates obtained in a three step censored quantile regression presented by Chernozhukov and Hong (2002).

Table 1: Village Level Demographic, Development, and Health Related Characteristics

	VAS-eligible	Non-VAS	P-value
Demographics[1]			
Village Population	2763	2794	0.835
< 6 years old	14.4%	14.1%	0.144
%Female of < 6 years old	48.5%	48.6%	0.646
Scheduled Caste	21.0%	21.3%	0.944
Schedules Tribe	14.9%	12.8%	0.148
Female Literacy	43.1%	44.3%	0.285
Population Employed	50.6%	49.8%	0.192
Development Indicators[2]			
Piped Water	49.7%	48.0%	0.684
Electricity in Majority of Households	95.0%	92.7%	0.236
Bank in Village	25.7%	37.7%	0.002
Distance to Nearest Town (KM)	13.3	12.3	0.176
All Weather Road In Village	85.3%	87.3%	0.477
Primary Health Center In Village	22.3%	20.0%	0.485
Private Clinic In Village	45.3%	41.7%	0.366
Health Behaviors[2]			
Majority of Men Heavy Drinkers	59.7%	53.7%	0.139
Majority Use Tobacco	67.3%	67.0%	0.931
Mortality Rate (2004-08)[3]			
Any Household Member	14.6%	14.1%	0.62
Female (aged 15-49)	1.4%	1.4%	0.99

[1] Data is taken from the 2001 census.

[2] Data is taken from the ASHA questionnaire (N=572)

[3] Data taken from District Level Health Survey Wave 3 collected in 2007-08.

Table 2: Summary of Data

Variables	Obs.	Mean	SD	Min	Max
Medical Cost Data					
Zero Medical Cost	6964	84%	0.439	0	1
OOP (Rs.)	6964	3555	14274	0	2,00,000
Has access to VAS?	6964	50%	0.5	0	1
Age Distribution within Households					
% of Household age 1 - 5 years	6964	7%	0.127	0	0.667
% of Household age 6 - 15 years	6964	15%	0.192	0	0.8
% of Household age 16 - 65 years	6964	73%	0.232	0	1
% of Household age 65+	6964	5%	0.132	0	1
Education					
Illiterate	6964	38%	0.293	0	1
Up to High School	6964	31%	0.297	0	1
Beyond High School	6964	31%	0.294	0	1
# of Adults in full time employment	6964	2.36	1.502	0	10
# of household members	6964	4.87	2.122	1	12

Note: OOP i.e. total out of pocket health costs are the sum of health expenditures at the hospital, for purchasing medicines, and for diagnostics; OOP has been censored at Rs. 200,000, affecting 35 observations in the sample, i.e. 0.005 % of the sample.

Table 3A: Borrowed Money for "Health Reasons" In Past Year

Variables	Non-VAS	VAS	Difference
Borrowed Money (Y/N)	24.2%	20.7%	-3.5%***
Quantity Borrowed (in Rs.)			
All (set to 0 if no reported borrowing)	5065	4098	-967***
Conditional on Borrowing	20,926	19,727	-1,199**

*Note: *, **, and *** indicate 90%, 95%, and 99% levels of significance, respectively.*

Table 3B: Catastrophic Health Care Expenditures

% of Non-Food Expenditure Limit		Non-VAS	VAS	Difference
Percent reaching catastrophic limit	40%	3.41%	2.70%	-0.71% *
	50%	2.61%	2.22%	-0.39%
	60%	2.08%	1.68%	-0.40%
	70%	1.80%	1.34%	-0.46%
	80%	1.54%	0.91%	-0.63% **
Mean amount over catastrophic limit (Rs.)	40%	56,700.92	36,822.19	-19,878.73 **
	50%	66,307.45	36,862.71	-29,444.75 **
	60%	75,415.93	40,356.36	-35,059.58 **
	70%	80,362.84	43,215.88	-37,146.96 **
	80%	86,913.19	56,292.79	-30,620.40
% of Total Expenditure Limit		**Non-VAS**	**VAS**	**Difference**
Percent reaching catastrophic limit	10%	10.09%	10.03%	-0.05%
	20%	6.38%	5.92%	-0.46%
	30%	4.49%	3.89%	-0.60%
	40%	3.34%	2.58%	-0.76% *
	50%	2.55%	2.09%	-0.45%
Mean amount over catastrophic limit (Rs.)	10%	31,983.49	21,313.18	-10,670.31 ***
	20%	40,554.01	26,232.83	-14,321.17 **
	30%	48,536.53	30,760.43	-17,776.10 **
	40%	56,974.87	37,489.47	-19,485.41 **
	50%	66,712.53	37,690.21	-29,022.32 **

*Note: *, **, and *** indicate 90%, 95%, and 99% levels of significance, respectively. The amount payed over the catastrophic limit is conditional on reaching the catastrophic limit.*

Table 4: Key Estimates of the Distributional Effects of access to Insurance on Out of Pocket Spending

	Conditional Estimates Using Koenker & Basset Estimator		Unconditional Estimates Using Chernozhukov & Hong Estimator	
Quantile	δ Estimate (Effect of VAS)	Standard Error	β Estimate (Effect of VAS)	Standard Error
5	-529.99**	215.56	0	0
10	-711.76***	243.99	0	0
15	-876.62**	343.74	0	0
25	-1,485.29***	459.92	0	0
40	-2,197.19***	495.55	0	0
50	-2,878.92***	706.33	0	0
60	-2,589.79**	1,242.94	0	0
75	-4,484.71***	1,340.32	0	0
85	-6,408.61*	3,600.68	802.20**	365.61
90	-4,941.37	5,196.11	-1,026.96	705.06
95	-23,548.19***	8,199.09	-3,906.08**	1,748.25

Note: Parameter estimates were predicted using the models presented in Koenker & Basset (1976) and Chernozhukov & Hong (2002)

Table 5: Estimates of the Value of Insurance (Rs.)

Subsistence Consumption Level	Income	Asset Protection	Consumption Smoothing (γ=0)	Total Insurance Value (γ=0)	Consumption Smoothing (γ=3)	Total Insurance Value (γ=3)	Consumption Smoothing (γ=4)	Total Insurance Value (γ=4)	Consumption Smoothing (γ=5)	Total Insurance Value (γ=5)
Poverty Line	Food Subsistence	463.44	0.00	463.44	0.00	463.44	0.00	463.44	0.00	463.44
	Poverty Line	463.44	0.00	463.44	0.00	463.44	0.00	463.44	0.00	463.44
	Median	278.06	185.37	463.44	387.29	665.35	509.98	788.04	678.48	956.54
	75th Percentile	278.06	185.37	463.44	268.22	546.28	305.92	583.98	350.25	628.32
Finkelstein McKnight Truncation	Food Subsistence	351.47	111.97	463.44	667.83	1,019.30	1,148.46	1,499.93	1,327.07	1,678.54
	Poverty Line	278.06	185.38	463.44	797.03	1,075.09	1,396.37	1,674.43	2,410.90	2,688.96
	Median	278.06	185.37	463.44	387.29	665.35	509.98	788.04	678.48	956.54
	75th Percentile	278.06	185.37	463.44	268.22	546.28	305.92	583.98	350.25	628.32
Food Expenditure	Food Subsistence	463.44	0.00	463.44	0.00	463.44	0.00	463.44	0.00	463.44
	Poverty Line	350.26	113.18	463.44	217.99	568.25	276.97	627.23	353.56	703.82
	Median	278.06	185.37	463.44	387.29	665.35	509.98	788.04	678.48	956.54
	75th Percentile	278.06	185.37	463.44	268.22	546.28	305.92	583.98	350.25	628.32

Appendix

Appendix A: Full OOP Distributions

	Conditional Distribution Using Koenker & Basset Estimator		Unconditional Distribution Using Chernozhukov & Hong Estimator	
Quantile	**VAS**	**No VAS**	**VAS**	**No VAS**
1	396	925	0	0
2	558	1,061	0	0
3	722	1,100	0	0
4	849	1,274	0	0
5	1,023	1,545	0	0
6	1,280	1,724	0	0
7	1,399	1,840	0	0
8	1,578	2,113	0	0
9	1,728	2,311	0	0
10	1,792	2,503	0	0
11	1,862	2,614	0	0
12	1,955	2,846	0	0
13	2,039	3,015	0	0
14	2,201	3,158	0	0
15	2,447	3,321	0	0
16	2,556	3,466	0	0
17	2,729	3,728	0	0
18	2,739	3,793	0	0
19	2,851	3,974	0	0
20	2,927	4,181	0	0
21	3,074	4,402	0	0
22	3,160	4,615	0	0
23	3,324	4,811	0	0
24	3,472	5,079	0	0
25	3,798	5,282	0	0
26	3,917	5,375	0	0
27	4,046	5,762	0	0
28	4,244	5,971	0	0
29	4,412	6,162	0	0
30	4,588	6,409	0	0
31	4,857	6,955	0	0
32	5,071	7,231	0	0
33	5,449	7,394	0	0
34	5,593	7,515	0	0

35	5,848	7,839	0	0
36	6,108	8,164	0	0
37	6,342	8,388	0	0
38	6,479	8,520	0	0
39	6,633	8,708	0	0
40	6,927	9,125	0	0
41	7,102	9,275	0	0
42	7,294	9,505	0	0
43	7,414	9,955	0	0
44	7,596	10,279	0	0
45	7,819	10,648	0	0
46	8,112	11,001	0	0
47	8,456	11,175	0	0
48	8,667	11,464	0	0
49	8,788	11,677	0	0
50	9,062	11,941	0	0
51	9,450	12,136	0	0
52	9,598	12,508	0	0
53	9,752	12,868	0	0
54	10,003	13,217	0	0
55	10,327	13,448	0	0
56	10,930	13,947	0	0
57	11,697	14,397	0	0
58	11,907	14,628	0	0
59	12,144	15,176	0	0
60	13,049	15,639	0	0
61	13,181	15,991	0	0
62	13,534	16,462	0	0
63	13,872	16,982	0	0
64	14,306	17,481	0	0
65	14,631	17,832	0	0
66	15,218	18,317	0	0
67	15,679	18,865	0	0
68	16,123	19,528	0	0
69	16,718	20,189	0	0
70	17,229	20,586	0	0
71	17,495	21,433	0	0
72	18,099	22,352	0	0
73	18,314	22,699	0	0
74	18,917	23,407	0	0
75	19,509	23,994	0	0
76	19,966	24,567	0	0
77	20,343	25,737	0	0

78	21,322	27,121	0	0
79	21,870	27,849	198	198
80	22,714	28,702	1,039	701
81	23,936	30,153	1,623	1,008
82	25,242	32,001	1,793	1,215
83	26,632	33,221	2,120	1,543
84	28,065	34,565	2,400	2,015
85	29,557	35,966	2,692	2,232
86	32,535	37,552	2,980	3,035
87	34,206	39,598	3,687	3,693
88	36,622	42,472	4,950	4,513
89	42,477	45,918	5,776	5,776
90	44,132	49,073	6,802	7,755
91	45,920	53,762	7,819	9,606
92	48,446	64,103	8,743	11,623
93	51,400	75,212	10,261	13,943
94	56,875	86,993	12,582	17,020
95	69,566	93,113	15,918	19,787
96	74,956	106,546	21,158	23,764
97	85,241	119,641	27,787	29,947
98	125,897	154,051	34,637	42,057
99	163,451	238,293	58,234	77,649

Appendix B: Quantile Regression Estimates Conditional on Having OOP

Quantile	$\delta_{1\tau}$ Estimate (Effect of VAS)	Standard Error	p-value	[95% Conf.	Interval]
1	-558.56	138.60	0.000	-830.41	-286.71
2	-503.20	199.76	0.012	-895.00	-111.40
3	-378.87	170.41	0.026	-713.10	-44.63
4	-425.86	198.70	0.032	-815.58	-36.15
5	-529.99	215.56	0.014	-952.77	-107.20
6	-444.76	241.44	0.066	-918.29	28.78
7	-441.20	208.07	0.034	-849.30	-33.10
8	-534.88	245.29	0.029	-1,015.98	-53.78
9	-583.37	236.59	0.014	-1,047.40	-119.33
10	-711.76	243.99	0.004	-1,190.29	-233.22
11	-751.72	237.80	0.002	-1,218.12	-285.32
12	-891.60	262.51	0.001	-1,406.47	-376.73
13	-977.82	300.97	0.001	-1,568.11	-387.53
14	-958.40	290.78	0.001	-1,528.71	-388.09
15	-876.62	343.74	0.011	-1,550.80	-202.44
16	-910.48	351.59	0.010	-1,600.07	-220.90
17	-999.24	323.46	0.002	-1,633.65	-364.83
18	-1,054.04	271.83	0.000	-1,587.18	-520.89
19	-1,122.84	308.87	0.000	-1,728.63	-517.06
20	-1,253.98	271.95	0.000	-1,787.36	-720.61
21	-1,327.88	388.36	0.001	-2,089.58	-566.17
22	-1,455.64	438.65	0.001	-2,315.96	-595.31
23	-1,487.14	372.02	0.000	-2,216.78	-757.49
24	-1,608.53	444.59	0.000	-2,480.50	-736.56
25	-1,485.29	459.92	0.001	-2,387.34	-583.24
26	-1,459.05	443.76	0.001	-2,329.40	-588.69
27	-1,716.15	501.65	0.001	-2,700.05	-732.25
28	-1,727.80	557.54	0.002	-2,821.30	-634.29
29	-1,750.52	593.01	0.003	-2,913.61	-587.43
30	-1,821.35	593.22	0.002	-2,984.84	-657.85
31	-2,098.43	643.41	0.001	-3,360.35	-836.50
32	-2,160.35	667.76	0.001	-3,470.04	-850.66
33	-1,945.53	578.07	0.001	-3,079.31	-811.74
34	-1,921.86	527.60	0.000	-2,956.65	-887.07
35	-1,990.49	529.89	0.000	-3,029.76	-951.21
36	-2,055.78	563.95	0.000	-3,161.87	-949.69
37	-2,046.79	456.34	0.000	-2,941.83	-1,151.76
38	-2,040.94	436.76	0.000	-2,897.57	-1,184.31

39	-2,075.07	395.38	0.000	-2,850.54	-1,299.60
40	-2,197.19	495.55	0.000	-3,169.12	-1,225.25
41	-2,173.11	618.06	0.000	-3,385.32	-960.90
42	-2,211.43	623.09	0.000	-3,433.51	-989.35
43	-2,540.42	567.69	0.000	-3,653.83	-1,427.00
44	-2,683.31	690.63	0.000	-4,037.86	-1,328.76
45	-2,829.30	741.16	0.000	-4,282.96	-1,375.64
46	-2,888.97	624.04	0.000	-4,112.91	-1,665.02
47	-2,719.48	541.51	0.000	-3,781.55	-1,657.41
48	-2,796.27	597.18	0.000	-3,967.53	-1,625.01
49	-2,888.22	540.47	0.000	-3,948.26	-1,828.18
50	-2,878.92	706.33	0.000	-4,264.25	-1,493.58
51	-2,685.81	654.42	0.000	-3,969.34	-1,402.29
52	-2,909.87	685.97	0.000	-4,255.28	-1,564.46
53	-3,115.68	769.35	0.000	-4,624.62	-1,606.73
54	-3,214.30	653.27	0.000	-4,495.56	-1,933.03
55	-3,121.00	904.25	0.001	-4,894.53	-1,347.47
56	-3,016.77	1,069.65	0.005	-5,114.69	-918.85
57	-2,699.69	1,143.15	0.018	-4,941.77	-457.61
58	-2,721.12	1,059.72	0.010	-4,799.57	-642.67
59	-3,031.42	1,035.98	0.003	-5,063.31	-999.54
60	-2,589.79	1,242.94	0.037	-5,027.59	-151.99
61	-2,809.52	1,020.56	0.006	-4,811.15	-807.88
62	-2,927.58	1,028.39	0.004	-4,944.58	-910.58
63	-3,110.78	1,160.03	0.007	-5,385.97	-835.59
64	-3,174.20	1,174.51	0.007	-5,477.78	-870.62
65	-3,201.45	1,406.48	0.023	-5,960.01	-442.90
66	-3,099.42	1,539.05	0.044	-6,117.98	-80.85
67	-3,185.88	1,385.32	0.022	-5,902.93	-468.82
68	-3,405.12	1,600.62	0.034	-6,544.44	-265.80
69	-3,470.95	1,440.93	0.016	-6,297.07	-644.82
70	-3,356.30	1,373.50	0.015	-6,050.18	-662.43
71	-3,937.37	1,523.43	0.010	-6,925.30	-949.44
72	-4,253.12	1,167.88	0.000	-6,543.70	-1,962.55
73	-4,384.82	1,104.36	0.000	-6,550.81	-2,218.82
74	-4,490.25	1,540.91	0.004	-7,512.46	-1,468.04
75	-4,484.71	1,340.32	0.001	-7,113.49	-1,855.92
76	-4,600.52	1,617.60	0.005	-7,773.16	-1,427.89
77	-5,394.79	1,691.84	0.001	-8,713.03	-2,076.54
78	-5,799.29	1,933.50	0.003	-9,591.50	-2,007.07
79	-5,978.50	2,100.57	0.004	-10,098.38	-1,858.62
80	-5,988.29	2,215.02	0.007	-10,332.65	-1,643.94
81	-6,217.52	2,830.38	0.028	-11,768.79	-666.25

82	-6,759.39	2,291.33	0.003	-11,253.41	-2,265.36
83	-6,588.71	2,932.51	0.025	-12,340.29	-837.12
84	-6,500.02	2,553.70	0.011	-11,508.64	-1,491.39
85	-6,408.61	3,600.68	0.075	-13,470.69	653.46
86	-5,017.28	3,408.53	0.141	-11,702.50	1,667.94
87	-5,392.15	4,779.99	0.259	-14,767.23	3,982.93
88	-5,849.88	5,187.69	0.260	-16,024.58	4,324.82
89	-3,440.60	4,157.49	0.408	-11,594.76	4,713.55
90	-4,941.37	5,196.11	0.342	-15,132.60	5,249.86
91	-7,842.47	6,030.60	0.194	-19,670.40	3,985.45
92	-15,656.94	8,287.63	0.059	-31,911.61	597.73
93	-23,812.57	7,302.04	0.001	-38,134.18	-9,490.97
94	-30,118.10	7,331.10	0.000	-44,496.71	-15,739.49
95	-23,548.19	8,199.09	0.004	-39,629.21	-7,467.17
96	-31,589.46	13,104.10	0.016	-57,290.76	-5,888.16
97	-34,400.45	34,778.97	0.323	-102,613.00	33,812.15
98	-28,154.07	146,932.00	0.848	-316,334.40	260,026.30
99	-74,881.50	107,718.90	0.487	-286,152.40	136,389.40

Appendix C: Censored Quantile Regression Estimates

Quantile	$\beta_{1\tau}$ Estimate (Effect of VAS)	Standard Error	p-value	[95% Conf.	Interval]
1	0.03	0.04	0.443	-0.04	0.10
2	0.03	0.04	0.443	-0.04	0.10
3	0.03	0.04	0.443	-0.04	0.10
4	0.03	0.04	0.443	-0.04	0.10
5	0.03	0.04	0.443	-0.04	0.10
6	0.03	0.04	0.443	-0.04	0.10
7	0.03	0.04	0.443	-0.04	0.10
8	0.03	0.04	0.443	-0.04	0.10
9	0.03	0.04	0.443	-0.04	0.10
10	0.03	0.04	0.443	-0.04	0.10
11	0.03	0.04	0.443	-0.04	0.10
12	0.03	0.04	0.443	-0.04	0.10
13	0.03	0.04	0.443	-0.04	0.10
14	0.03	0.04	0.443	-0.04	0.10
15	0.03	0.04	0.443	-0.04	0.10
16	0.03	0.04	0.443	-0.04	0.10
17	0.03	0.04	0.443	-0.04	0.10
18	0.03	0.04	0.443	-0.04	0.10
19	0.03	0.04	0.443	-0.04	0.10
20	0.03	0.04	0.443	-0.04	0.10
21	0.03	0.04	0.443	-0.04	0.10
22	0.03	0.04	0.443	-0.04	0.10
23	0.03	0.04	0.443	-0.04	0.10
24	0.03	0.04	0.443	-0.04	0.10
25	0.03	0.04	0.443	-0.04	0.10
26	0.03	0.04	0.443	-0.04	0.10
27	0.03	0.04	0.443	-0.04	0.10
28	0.03	0.04	0.443	-0.04	0.10
29	0.03	0.04	0.443	-0.04	0.10
30	0.03	0.04	0.443	-0.04	0.10
31	0.03	0.04	0.443	-0.04	0.10
32	0.03	0.04	0.443	-0.04	0.10
33	0.03	0.04	0.443	-0.04	0.10
34	0.03	0.04	0.443	-0.04	0.10
35	0.03	0.04	0.443	-0.04	0.10
36	0.03	0.04	0.443	-0.04	0.10
37	0.03	0.04	0.443	-0.04	0.10

38	0.03	0.04	0.443	-0.04	0.10
39	0.03	0.04	0.443	-0.04	0.10
40	0.03	0.04	0.443	-0.04	0.10
41	0.03	0.04	0.443	-0.04	0.10
42	0.03	0.04	0.443	-0.04	0.10
43	0.03	0.04	0.443	-0.04	0.10
44	0.03	0.04	0.443	-0.04	0.10
45	0.03	0.04	0.443	-0.04	0.10
46	0.00	0.00	1.000	0.00	0.00
47	0.00	0.00	1.000	0.00	0.00
48	0.00	0.00	1.000	0.00	0.00
49	0.00	0.00	1.000	0.00	0.00
50	0.00	0.00	1.000	0.00	0.00
51	0.00	0.00	1.000	0.00	0.00
52	0.00	0.00	1.000	0.00	0.00
53	0.00	0.00	1.000	0.00	0.00
54	0.00	0.00	1.000	0.00	0.00
55	0.00	0.00	1.000	0.00	0.00
56	0.00	0.00	1.000	0.00	0.00
57	0.00	0.00	1.000	0.00	0.00
58	0.00	0.00	1.000	0.00	0.00
59	0.00	0.00	1.000	0.00	0.00
60	0.00	0.00	1.000	0.00	0.00
61	0.00	0.00	1.000	0.00	0.00
62	0.00	0.00	1.000	0.00	0.00
63	0.00	0.00	1.000	0.00	0.00
64	0.00	0.00	1.000	0.00	0.00
65	0.00	0.00	1.000	0.00	0.00
66	0.00	0.00	1.000	0.00	0.00
67	0.00	0.00	1.000	0.00	0.00
68	0.00	0.00	1.000	0.00	0.00
69	0.00	0.00	1.000	0.00	0.00
70	0.00	0.00	1.000	0.00	0.00
71	0.00	0.00	1.000	0.00	0.00
72	0.00	0.00	1.000	0.00	0.00
73	0.00	0.00	1.000	0.00	0.00
74	0.00	0.00	1.000	0.00	0.00
75	0.00	0.00	1.000	0.00	0.00
76	0.00	0.00	1.000	0.00	0.00
77	0.00	0.00	1.000	0.00	0.00
78	0.00	0.00	1.000	0.00	0.00
79	0.00	0.00	0.000	0.00	0.00
80	536.88	48.09	0.000	442.61	631.16

81	1,256.61	78.91	0.000	1,101.90	1,411.31
82	1,109.86	98.92	0.000	915.90	1,303.81
83	956.08	96.45	0.000	766.99	1,145.17
84	624.13	173.74	0.000	283.50	964.75
85	802.20	365.61	0.028	85.40	1,519.00
86	-78.79	290.43	0.786	-648.16	490.58
87	-8.16	455.03	0.986	-900.23	883.91
88	530.98	518.87	0.306	-486.20	1,548.17
89	0.00	603.35	1.000	-1,182.79	1,182.79
90	-1,026.96	705.06	0.145	-2,409.11	355.19
91	-1,850.36	920.86	0.045	-3,655.55	-45.16
92	-2,967.92	821.63	0.000	-4,578.58	-1,357.25
93	-3,726.70	1,158.54	0.001	-5,997.82	-1,455.59
94	-4,484.18	1,365.89	0.001	-7,161.77	-1,806.59
95	-3,906.08	1,748.25	0.025	-7,333.21	-478.95
96	-2,612.89	2,089.94	0.211	-6,709.84	1,484.06
97	-2,170.80	2,762.60	0.432	-7,586.38	3,244.78
98	-7,426.00	5,801.95	0.201	-18,799.66	3,947.66
99	-19,443.29	95,021.87	0.838	-205,716.30	166,829.70