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Financial risk protection from social health insurance

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ABSTRACT

This paper estimates the impact of social health insurance on financial risk 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 distributional impact of insurance on of out-of-pocket costs and incorporate these results with a stylized expected utility model to compute associated welfare effects. We adjust the standard model, accounting for conditions of developing countries by incorporating consumption floors, informal borrowing, and asset selling which allow us to separate the value of financial risk reduction from consumption smoothing and asset protection. Results show that insurance reduces out-of-pocket costs, particularly in higher quantiles of the distribution. We find reductions in the frequency and amount of money borrowed for health reasons. Finally, we find that the value of financial risk reduction outweighs total per household costs of the insurance program by two to five times.

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 et al., 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. (2013) 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 et al., 2013). 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 et al., 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 smooth-

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[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).

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ing covered between half and three quarters of the costs of the program (Finkelstein and McKnight, 2008). This 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 Bassett (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 Chernozhukov 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 and Gruber, 2002; Morduch, 1995). For example, households may self-insure and dis-save from their assets to smooth consumption (Rosenzweig and 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. 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 and 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; thus, 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 and Rao, 2012). (Morduch and Rutherford, 2003) review a number of empirical papers to show that such mechanisms rarely provide complete coverage. These gaps in informal insurance not only retard income growth possibilities but may lead to poverty traps (Zimmerman and 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 et al., 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 and Nagpal, 2012). Some evidence suggests that these programs have

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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 does not significantly 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 and 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 the 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 272 villages just north of the eligibility border and 300 villages just south side of the eligibility border (see Fig. 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. A propensity score matching algorithm was implemented prior to collecting any data and was based on the census data.[2] 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. 300 control villages from the south side were selected based on probability proportional to population size using 2001 Census data. Villages from the south side were matched with replacement to 272 villages from the VAS-eligible districts of Uttara Kannada, Haveri, and Bellary, on the basis of variables from the 2001 Census. 24 villages were sampled twice and one village was sampled five times. 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. Fig. 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. This suggests that the census data measurements we used to match villages before data collection were sufficient observables for matching and support the assumption of conditional independence discussed in (Caliendo and Kopeinig, 2008). 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.

Every household in the selected villages was asked to participate in a door to door enumeration survey where we verified poverty status, asked if anyone in the household had been admitted to a hospital and whether that visit was for a service potentially covered through VAS. Among these households in the study vil-

[2] To address the sensitivity of balance to various matching/sampling procedures, we conducted an exercise in which we calculated the L1 measure of imbalance under 3 different types of sample scenarios: 1) Our current propensity score matched sample; 2) we ran 500 simulations using CEM to match the 272 northern villages to 300 southern villages using the original census data (simulations were required since we were using the k2k command, which randomly drops matched villages so that the number of treatment and control villages are equal making the sample slightly different in each simulation and thus making the L1 slightly different); and 3) we ran 500 simulations, each of which randomly assigning 300 villages as hypothetical treatment villages and randomly assigning 300 villages as hypothetical control villages, regardless of geography. Scenario 3 simulates what balance might have looked like if we had been able to use the gold standard of random treatment assignment. We took the average of the 500 L1 measures produced in the simulations from scenarios 2 and 3. We found that the L1 measure for scenario 1 (our sample) was 0.756, and the mean L1s for scenarios 2 and 3 were 0.763 and 0.664, respectively (a lower L1 suggests better balance). This suggests that although we would have achieved better balance had we been able to randomly assign which villages had access to VAS, we would have achieved very similar balance (possible even slightly worse) if we had used the CEM method.

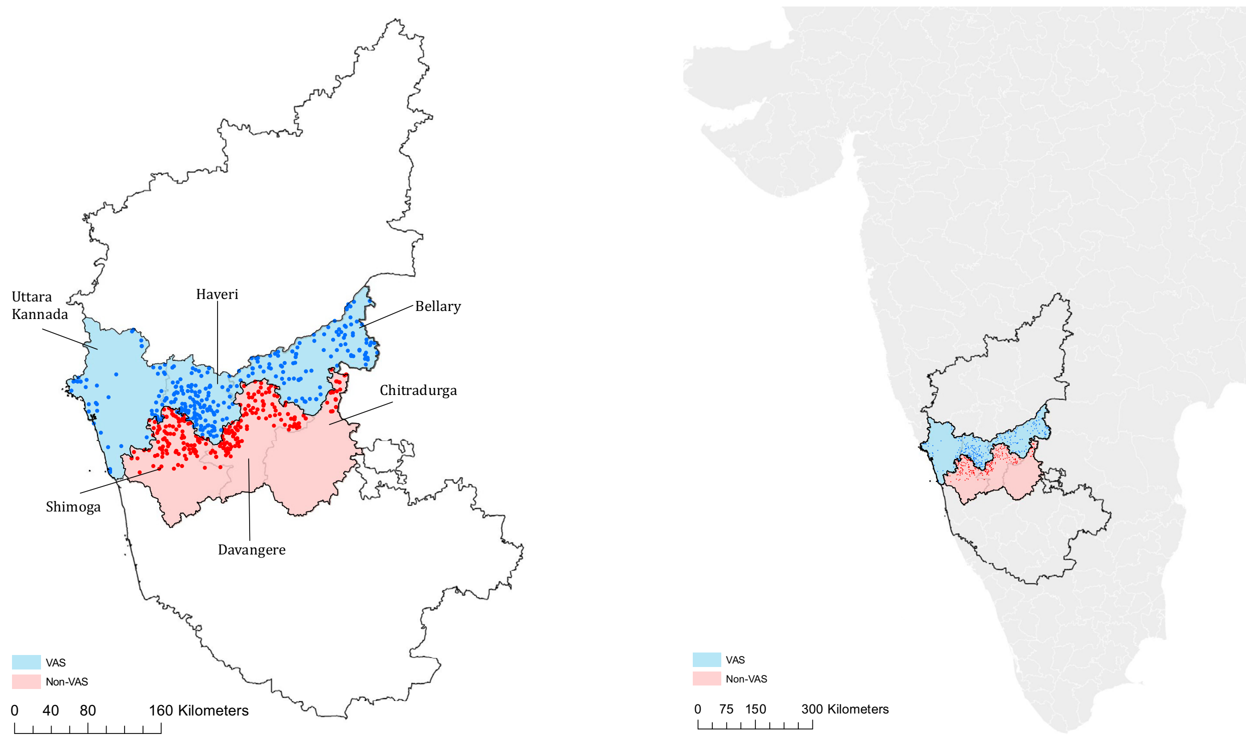


Fig. 1. Map of Study Area.

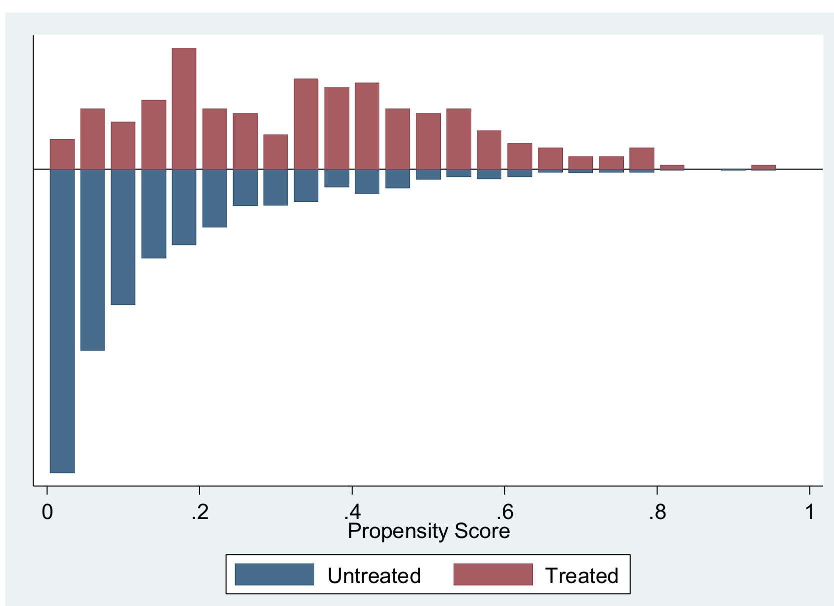


Fig. 2. Propensity Scores for villages with and without Health Insurance.
Note: Distribution of estimated propensity score for VAS (Treated) and non-VAS (Untreated) villages in our sample. The above diagram indicates we have extensive overlap in the range of propensity scores in both treated and untreated villages.

lages we 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 et al., 2009). We initially surveyed 22,796 BPL households that were eligible for VAS and 21,767 BPL households that were ineligible for VAS. From this we conducted an in-depth household survey with all households that reported a hospitalization for a covered condition and randomly selected households to survey from those with hospitalizations for non-covered conditions and households without hospitalizations. In all, we surveyed 6964 households with BPL cards from the treatment and control villages and asked questions about out-of-pocket costs for medical care. Of VAS eligible households our raw data contains 491 observations for covered conditions, 494 observations for non-covered conditions and 2502 observations of households without a hospitalization. Of

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

	VAS-eligible N = 272	Non-VAS N = 300	P-value
Demographics[a]			
Mean Village Population	2763	2794	0.835
Mean% of village population < 6 years old	14.4%	14.1%	0.144
Mean% Female of < 6 years old population	48.5%	48.6%	0.646
Mean% of village population that is Scheduled Caste	21.0%	21.3%	0.944
Mean% of village population that is Scheduled Tribe	14.9%	12.8%	0.148
Mean Female Literacy Rate	43.1%	44.3%	0.285
Mean% Population Employed	50.6%	49.8%	0.192
Development Indicators[b]			
% Villages with Piped Water	49.7%	48.0%	0.684
% Villages with Electricity in Majority of Households	95.0%	92.7%	0.236
% Villages with Bank	25.7%	37.7%	0.002
Mean Distance to Nearest Town (KM)	13.3	12.3	0.176
% Villages with All Weather Road	85.3%	87.3%	0.477
% Villages with Primary Health Center	22.3%	20.0%	0.485
% Villages with Private Clinic	45.3%	41.7%	0.366
Health Behaviors[b]			
% Villages where Majority of Men Heavy Drinkers	59.7%	53.7%	0.139
% of Villages where Majority Use Tobacco	67.3%	67.0%	0.931
Mortality Rate (2004–08)[c]			
Mean District Rate Among Any Household Member	14.6%	14.1%	0.62
Mean District Rate Among Female (aged 15–49)	1.4%	1.4%	0.99

[a] *Source:* 2001 Census of India; data from propensity score matched villages indicating no observable differences on the variables used in the propensity score model.
[b] *Source:* Community health worker survey; these variables were not used to build the propensity score model. For measures of Health Behaviors, majority is qualitative. The community health worker was asked whether most men were heavy drinkers and whether most people were smokers.
[c] *Source:* District Level Health Survey Wave 3; using a Government of India household survey that is designed to be representative at the district level we show that there are no pre-VAS roll-out differences in mortality rates across the VAS roll-out boundary.

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: Summary stats are weighted to account for oversampling. 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.

ineligible households, our raw data contains 495 observations of covered conditions, 416 observations of non-covered conditions and 2566 observations of households without a hospitalization. Because households with a hospitalization were over-sampled, 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 weighted summary statistics from our data. In our sample of 6964 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. 3555, 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

4.1. Distribution of out-of-pocket health care costs

In line with the existing literature reviewed in (Acharya et al., 2012), 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). In our analysis, 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%–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 explicitly model the conditional mean. Koenker and Bassett (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 and Bassett, 1978). This approach has been used to study the impact of an expansion in health insurance on out-of-pocket costs (Engelhardt and Gruber, 2011; Finkelstein and McKnight, 2008). One aspect of the out-of-pocket spending pattern that remains unexplored in these papers is the presence of excess zeros and the 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 et al., 1983). Powell extended the framework developed by Koenker and Bassett (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 and 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 OOPi measures the out-of-pocket health costs for household i, VASi is a binary indicator of access to the health insurance scheme, xi 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 $\beta1\tau$ that measures the impact of access to VAS on out-of-pocket health costs at the τ^{th} quantile. Here, identification of $\beta1\tau$ 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 Bassett (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 $\delta1\tau$. 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.

4.2. Stylized utility model

Changes in the distribution of out-of-pocket costs may imply changes in welfare for risk-averse households; in this section we extend the standard model to quantify potential welfare gains from a change in the distribution of out-of-pocket costs. 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 costs of health shocks with and without insurance coverage (Engelhardt and Gruber, 2011; Feldstein and Gruber, 1995; Finkelstein and 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 and 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 has a stock of wealth which is 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, $u(C)$, where utility is concave in consumption (i.e. $u'(.) > 0$; $u''(.) < 0$. The utility function takes the form:

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

where γ is the relative risk aversion parameter of the household. The household faces a risk of poor health that requires medical 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 $[0,\infty]$.

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. The second departure we make is assuming 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. 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. We label this adjustment to wealth holding W_{adj}. Thus, the household's consumption and wealth adjustment can be written as:

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

$$W_{adj} = \begin{cases} (1-x) * OOP, & M - x * OOP \geq \bar{C} \\ (1-x) * OOP + \bar{C} - (M - x * OOP), & M - x * OOP < \bar{C} \end{cases}$$

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 and 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 ($x = 40\%$).

The total amount a household would be willing to pay to avoid a health shock can be written in two parts:

$$V = \pi + E\left(W_{adj}\right)$$

Where π is the value of consumption smoothing of not facing any out of pocket costs, and is captured by:

$$U\left(M - \pi^{NoVAS} | VAS = 0\right) = \int_0^{\frac{M-\bar{C}}{x}} U\left(M - x * OOP\right) f\left(OOP\right) dOOP$$
$$+ U\left(\bar{C}\right) * P(C = \bar{C} | VAS = 0)$$

And $E(W_{adj})$ is the expected wealth adjustment the household would no longer have to face and is written as:

$$E\left(W_{adj}^{NoVAS} | VAS = 0\right) = \int_0^{\frac{M-\bar{C}}{x}} (1 - x)\, OOP * f\left(OOP\right) dOOP$$
$$+ \int_{\frac{M-\bar{C}}{x}}^{\infty} \left(OOP + \bar{C} - M\right) f\left(OOP\right) dOOP$$

Where $P\left(C = \bar{C}\right)$ is the probability of the household incurring a health cost so large that their consumption hits the consumption floor and is dependent upon the healthcare cost distribution, $f(OOP)$. Note that this expected utility of consumption smoothing and expected value of wealth adjustment 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. The above equations capture the value of consumption smoothing and expected wealth adjustment when there is no access to health insurance (VAS = 0) and households face the out-of-pocket cost distribution, $f\left(OOP\right)$. Similarly, if the healthcare cost distribution associated with access to VAS is captured by $g(OOP)$ then the counterfactual money value of consumption smoothing is captured by:

$$U\left(M - \pi^{VAS} | VAS = 1\right) = \int_0^{\frac{M-\bar{C}}{x}} U\left(M - x * OOP\right) g\left(OOP\right) dOOP$$
$$+ U\left(\bar{C}\right) * P(C = \bar{C} | VAS = 1)$$

And the expected wealth adjustment that the household with access to VAS faces can be written as:

$$E\left(W_{adj}^{VAS} | VAS = 1\right) = \int_0^{\frac{M-\bar{C}}{x}} (1 - x)\, OOP * g\left(OOP\right) dOOP$$
$$+ \int_{\frac{M-\bar{C}}{x}}^{\infty} \left(OOP + \bar{C} - M\right) g\left(OOP\right) dOOP$$

The total willingness to pay to avoid out of pocket costs from health shocks is the sum of π and $E\left(W_{adj}\right)$. Access to insurance changes the out of pocket cost distribution a household faces which changes a household's willingness to pay to avoid out of pocket health costs. This change in willingness to pay is the total value of the insurance program:

$$\Delta V = \Delta\pi + \Delta E(W_{adj})$$

Where $\Delta\pi = \pi^{NoVAS} - \pi^{VAS}$ is the value of consumption smoothing and $\Delta E\left(W_{adj}\right) = E(W_{adj}^{NoVAS}) - E\left(W_{adj}^{VAS}\right)$ is the value of asset protection. 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

5.1. 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. 1199 less than those who did not have access to the scheme although the result is not significant.

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.

5.2. 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

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

Variables	Non-VAS	VAS	Difference
Borrowed Money (Y/N) N = 6964	24.2%	20.7%	−3.5%***
Quantity Borrowed (in Rs.)			
All (set to 0 if no reported borrowing) N = 6964	5065	4098	−967***
Conditional on Borrowing N = 1951	20,926	19,727	−1199

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	**

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

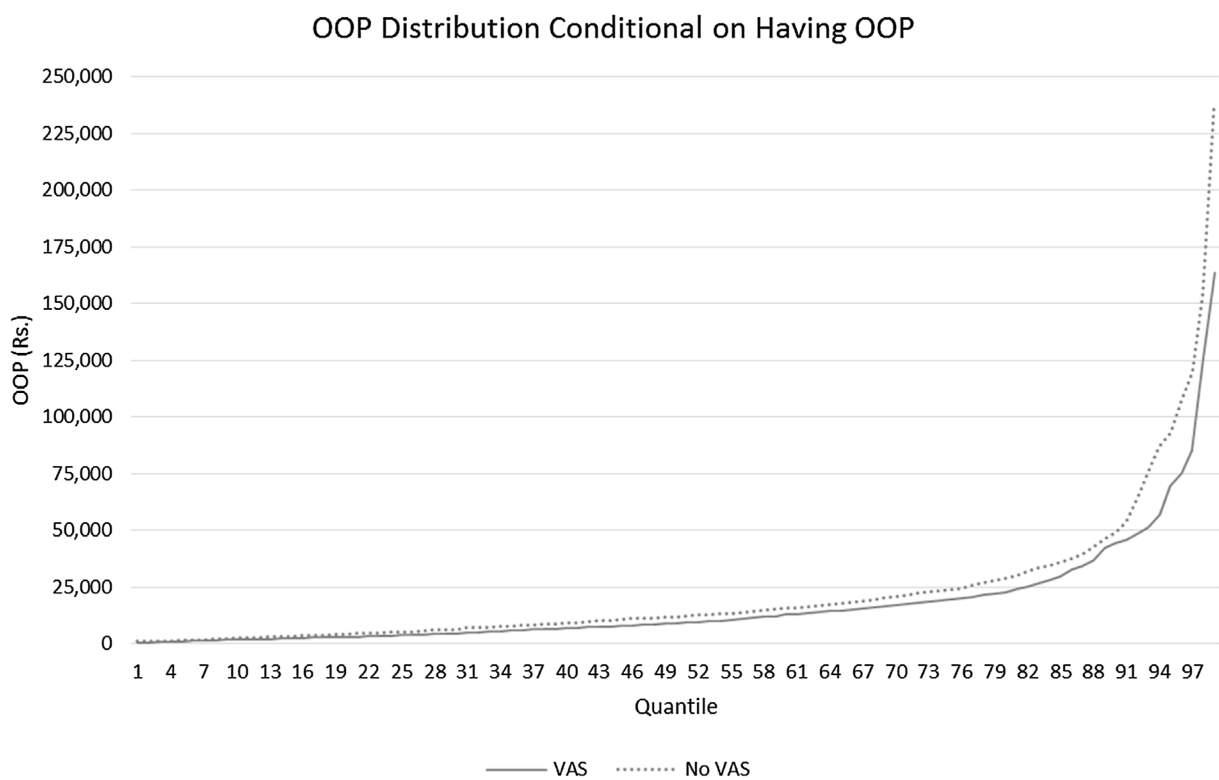
	Conditional Estimates Using Koenker & Basset Estimator		Unconditional Estimates Using Chernozhukov & Hong Estimator	
Quantile	δ Estimate (Effect of VAS)	Standard Error	β Estimate (Effect of VAS)	Standard Error
5	−529.99**	215.56	0	0
10	−711.76***	243.99	0	0
15	−876.62**	343.74	0	0
25	−1,485.29***	459.92	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 and Bassett (1978) and Chernozhukov and Hong (2002).

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. 2879 while the reduction in out-of-pocket expenditure at the 75th quantile is Rs. 4485. 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. 1257 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. 4484 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 et al., 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.

Fig. 3A and B shows these estimates graphically. Fig. 3A plots the distribution of out-of-pocket payments conditional on hav-

A



B

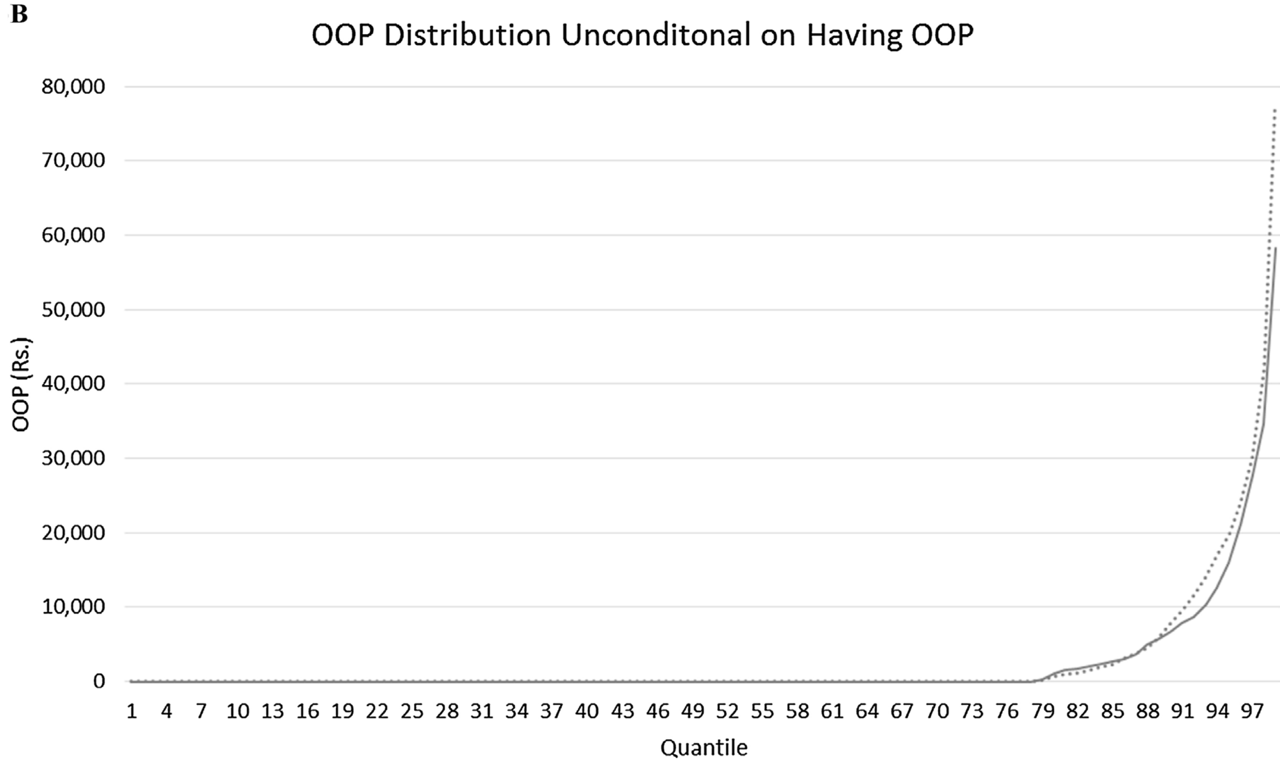


Fig. 3. (A) Aut of Pocket Cost Distribution conditional on having a health shock.
Note: Graph was created using values predicted from parameter estimates obtained in a quantile regression developed by Koenker and Bassett (1978) that has been run conditional on households experiencing any health costs.
(B) But 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).

ing 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. Fig. 3B plots the unconditional distribution of out-of-pocket payments. We find similar patterns here as in Fig. 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. 5203. 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. We test our results for robustness to the exclusion of right tails of matched propensity scores. We repeat the analysis, trimming households from the data whose matched village propensity scores have more than a 7%, 5%, and 3.8% probability difference in their propensity scores. We find that at every cut off level for trimming by propensity scores we find similar results to our main analysis for both the estimates of conditional and unconditional distributions of out of pocket costs. These results can be found in Appendices D and E.

5.3. Welfare calculations

We implement the algorithm described in the methods section and calculate $\Delta\pi$ and ΔW_{adj} 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 and 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 ($\gamma = 0$), 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. 1075 per household. Existing literature on risk aversion in developing economies state that poor households are likely to be highly risk adverse, taking all possible options to keep consumption above subsistence level (Alderman and Paxson, 1994; Chetty and Looney, 2006; Dercon, 2002). Similarly, Haushofer and Fehr (2014) find that poverty causes stress that leads to short sightedness and high levels of risk aversion in decision making (Haushofer and Fehr, 2014). The BPL households in our sample, with a much lower average income than the sample studied in Limwattananon et al. (2015), likely 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. 2689.

As income increases within a given level of risk aversion and subsistence consumption level, the total value of the insurance first rises and 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 and 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

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

Notes: Estimates of the value of the Vajpayee Arogyashree Scheme are derived from the estimates of the distribution of out of pocket costs for those with and without access to the scheme. We calculate the value of asset protection (ΔW_{adj} in the empirical model) and consumption smoothing ($\Delta\pi$ in the empirical model) at different levels of subsistence consumption and income levels.

20–40%; 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. More comprehensive insurance programs may counter behavioral hazard from underuse of care but also have more incentives that lead to increased moral hazard from overuse of care. VAS's 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. However, patients with asymptomatic conditions that could still lead to expensive hospitalizations if left untreated are not more likely to seek care. 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 et al. (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 et al., 2015). Basu et al. (2015) find that access to VAS for cardiac care was associated with about 2077 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. Another avenue through which access to VAS insurance could have welfare gains is through the "peace of mind" associated with access to insurance and studied by (Finkelstein et al., 2012) in the case of the Oregon health insurance experiment. As the population we study is likely very risk averse, welfare gains from knowing care is accessible could be significant. There also could be welfare gains if families had extended networks and financed their OOP by borrowing from across the north-south border as reductions in borrowing from friends and family in the south due to VAS could be significant.

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. 5203. 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 and

Gruber, 2011; Finkelstein and 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. Broader insurance programs could have various supply side responses, as noted in (Kondo and Shigeoka, 2013) where increased insurance coverage led to increases in hospital beds but no increases in the number of physicians and nurses. The relatively small subset of conditions covered by VAS combined with clearly defined care packages make these supply effects not an important consideration. In addition, social health insurance schemes have implications for precautionary savings which could affect the welfare effects of a program (Chou et al., 2003). However, we believe that precautionary saving is not a large concern for our population, who are mostly impoverished and with poor access to banks. 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). Another limitation of our study is that falsification of BPL cards is an issue in India. Ram et al. (2009) look at the distribution of BPL cards in Karnataka and find that 52% of BPL cards in Karnataka belong to people classified as non-poor (in the top 3 wealth quintiles) (Ram et al., 2009). They do not specify the distribution of cards by district thus we are unable to verify whether the problem of BPL card falsification is different across districts.

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 lifesaving 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. Another potential avenue for research is to study the distribution of welfare effects across households.

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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	1061	0	0
3	722	1100	0	0
4	849	1274	0	0
5	1023	1545	0	0
6	1280	1724	0	0
7	1399	1840	0	0
8	1578	2113	0	0
9	1728	2311	0	0
10	1792	2503	0	0
11	1862	2614	0	0
12	1955	2846	0	0
13	2039	3015	0	0
14	2201	3158	0	0
15	2447	3321	0	0
16	2556	3466	0	0
17	2729	3728	0	0
18	2739	3793	0	0
19	2851	3974	0	0
20	2927	4181	0	0
21	3074	4402	0	0
22	3160	4615	0	0
23	3324	4811	0	0
24	3472	5079	0	0
25	3798	5282	0	0
26	3917	5375	0	0
27	4046	5762	0	0
28	4244	5971	0	0
29	4412	6162	0	0
30	4588	6409	0	0
31	4857	6955	0	0
32	5071	7231	0	0
33	5449	7394	0	0
34	5593	7515	0	0
35	5848	7839	0	0
36	6108	8164	0	0
37	6342	8388	0	0
38	6479	8520	0	0
39	6633	8708	0	0
40	6927	9125	0	0
41	7102	9275	0	0
42	7294	9505	0	0
43	7414	9955	0	0
44	7596	10,279	0	0
45	7819	10,648	0	0
46	8112	11,001	0	0
47	8456	11,175	0	0
48	8667	11,464	0	0
49	8788	11,677	0	0
50	9062	11,941	0	0
51	9450	12,136	0	0
52	9598	12,508	0	0
53	9752	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	1039	701
81	23,936	30,153	1623	1008
82	25,242	32,001	1793	1215
83	26,632	33,221	2120	1543
84	28,065	34,565	2400	2015
85	29,557	35,966	2692	2232
86	32,535	37,552	2980	3035
87	34,206	39,598	3687	3693
88	36,622	42,472	4950	4513
89	42,477	45,918	5776	5776
90	44,132	49,073	6802	7755
91	45,920	53,762	7819	9606
92	48,446	64,103	8743	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

Appendix D. Conditional Quantile Regression Estimates, Propensity Scores Tails Excluded.

	7% Cut Off		5% Cut Off		3.8% Cut Off	
Quantile	$\delta_{1\tau}$ Estimate (Effect of VAS)	P-Value	$\delta_{1\tau}$ Estimate (Effect of VAS)	P-Value	$\delta_{1\tau}$ Estimate (Effect of VAS)	P-Value
1	−613.52	0.000	−613.52	0.000	−596.57	0.000
2	−489.35	0.028	−499.31	0.027	−550.80	0.032
3	−363.09	0.043	−363.09	0.043	−384.74	0.041
4	−412.73	0.042	−403.34	0.038	−357.79	0.086
5	−446.88	0.036	−451.18	0.035	−384.32	0.090
6	−356.23	0.091	−353.93	0.088	−349.41	0.106
7	−392.96	0.052	−392.96	0.058	−362.28	0.110
8	−397.56	0.095	−393.13	0.088	−399.64	0.131
9	−578.94	0.005	−579.02	0.005	−568.63	0.025
10	−638.91	0.002	−612.87	0.003	−596.90	0.011
11	−728.39	0.002	−658.87	0.000	−586.66	0.000
12	−747.83	0.003	−700.66	0.005	−594.02	0.010
13	−909.02	0.001	−906.45	0.001	−794.56	0.001
14	−973.86	0.016	−968.93	0.026	−870.07	0.047
15	−1214.27	0.000	−1214.11	0.000	−976.60	0.003
16	−1185.87	0.000	−1186.67	0.000	−1148.24	0.000
17	−1261.86	0.000	−1227.66	0.000	−1138.46	0.000
18	−1319.06	0.000	−1272.21	0.000	−1167.29	0.000
19	−1292.41	0.000	−1265.44	0.000	−1335.31	0.000
20	−1436.90	0.000	−1400.20	0.000	−1527.08	0.000
21	−1466.14	0.000	−1452.17	0.000	−1526.45	0.000
22	−1596.84	0.000	−1521.40	0.000	−1601.65	0.000
23	−1593.79	0.000	−1620.88	0.000	−1565.15	0.000
24	−1725.16	0.000	−1694.06	0.000	−1517.29	0.001
25	−1852.70	0.000	−1860.23	0.000	−1595.26	0.000
26	−1889.17	0.000	−1825.21	0.000	−1819.30	0.000
27	−2096.55	0.000	−1944.94	0.000	−1811.49	0.000
28	−1855.41	0.000	−1924.40	0.001	−1614.03	0.017
29	−1843.00	0.002	−1929.12	0.002	−1727.27	0.001
30	−1998.73	0.000	−1901.89	0.002	−1768.63	0.001
31	−1866.57	0.002	−1855.73	0.001	−1777.99	0.014
32	−1937.23	0.001	−1975.55	0.000	−1674.99	0.029
33	−2100.04	0.000	−2089.07	0.000	−1925.83	0.001
34	−2033.23	0.000	−2048.08	0.000	−1931.93	0.001
35	−2047.57	0.000	−1990.90	0.000	−1967.19	0.000
36	−2068.87	0.001	−2105.31	0.000	−2099.77	0.000
37	−2013.80	0.000	−1970.92	0.000	−1943.68	0.000
38	−2126.03	0.000	−2058.19	0.000	−1997.24	0.000
39	−2189.34	0.000	−2233.21	0.000	−1972.74	0.000
40	−2268.45	0.000	−2305.91	0.000	−1975.76	0.000
41	−2250.57	0.000	−2213.34	0.000	−1877.57	0.000

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42	−2167.61	0.004	−2294.80	0.000	−1915.35	0.002
43	−2371.75	0.000	−2245.63	0.003	−2093.17	0.002
44	−2524.82	0.000	−2356.46	0.001	−2013.01	0.002
45	−2668.00	0.000	−2483.54	0.000	−2049.64	0.010
46	−2777.06	0.000	−2458.52	0.002	−2325.02	0.015
47	−2517.33	0.000	−2552.46	0.000	−2229.01	0.006
48	−2542.91	0.000	−2605.82	0.000	−2563.49	0.000
49	−2630.64	0.000	−2778.69	0.000	−2436.52	0.000
50	−2753.94	0.000	−2871.92	0.001	−2720.41	0.000
51	−2717.35	0.000	−2867.51	0.001	−2899.20	0.000
52	−2758.63	0.000	−2918.33	0.000	−3142.66	0.000
53	−2737.71	0.000	−2882.72	0.000	−2994.62	0.000
54	−2495.72	0.002	−2662.14	0.001	−2699.25	0.000
55	−2552.59	0.000	−2725.27	0.000	−2675.41	0.001
56	−2686.05	0.014	−2866.45	0.003	−2334.54	0.039
57	−2891.75	0.017	−2870.19	0.006	−1918.84	0.070
58	−2786.30	0.015	−2736.81	0.013	−1644.11	0.059
59	−2772.97	0.014	−2649.78	0.020	−1846.24	0.050
60	−3032.41	0.003	−3061.52	0.002	−2057.69	0.035
61	−3078.01	0.005	−2990.76	0.005	−2026.52	0.014
62	−2899.69	0.002	−3156.83	0.004	−2035.18	0.047
63	−3202.22	0.008	−3346.21	0.002	−2143.45	0.112
64	−3197.22	0.016	−3252.18	0.018	−2922.69	0.046
65	−3040.01	0.021	−3191.43	0.020	−3033.02	0.047
66	−3147.70	0.018	−3662.21	0.023	−2982.01	0.047
67	−3150.81	0.051	−3558.98	0.019	−2868.40	0.042
68	−2930.08	0.076	−3288.23	0.011	−3210.95	0.043
69	−3188.82	0.021	−3383.42	0.031	−3056.30	0.058
70	−3484.83	0.020	−3786.32	0.014	−3358.28	0.015
71	−3472.92	0.007	−3846.85	0.014	−3600.86	0.008
72	−4185.66	0.006	−4633.40	0.003	−3657.78	0.024
73	−4530.15	0.002	−5079.23	0.002	−3679.97	0.005
74	−5012.27	0.000	−5236.19	0.000	−3784.90	0.007
75	−5016.95	0.000	−5126.97	0.000	−3575.46	0.014
76	−5092.07	0.003	−5395.95	0.005	−3356.02	0.026
77	−5418.39	0.016	−5745.93	0.005	−3615.80	0.096
78	−4743.91	0.021	−5025.64	0.019	−4303.04	0.035
79	−5252.35	0.016	−5423.71	0.020	−4700.01	0.012
80	−6451.69	0.005	−6656.02	0.006	−4635.49	0.077
81	−7113.06	0.006	−7834.42	0.001	−6852.28	0.013
82	−7743.15	0.000	−7912.57	0.000	−6688.31	0.012
83	−7088.60	0.012	−7544.64	0.006	−5508.55	0.079
84	−6843.82	0.015	−6972.70	0.033	−5678.48	0.046
85	−6479.23	0.082	−6798.01	0.045	−4423.75	0.111
86	−7356.31	0.023	−7502.34	0.027	−4934.10	0.144
87	−7072.60	0.073	−7209.94	0.087	−4866.88	0.271
88	−7059.07	0.146	−6830.34	0.141	−4853.69	0.270
89	−7734.30	0.127	−8372.38	0.113	−4209.37	0.406
90	−9142.30	0.055	−8991.45	0.053	−7348.65	0.177
91	−11643.46	0.056	−13368.53	0.028	−10688.79	0.147
92	−22769.29	0.001	−24810.67	0.000	−17931.36	0.019
93	−27383.58	0.000	−27628.21	0.000	−21598.82	0.011
94	−32923.57	0.000	−32628.28	0.000	−24127.69	0.004
95	−29961.33	0.000	−31747.73	0.000	−25489.09	0.017
96	−33674.62	0.014	−33126.01	0.013	−25359.87	0.068
97	−34939.74	0.409	−35608.45	0.457	−30241.96	0.523
98	−20315.93	0.883	−20630.99	0.881	−17358.29	0.892
99	−63757.21	0.614	−63181.48	0.618	−59412.73	0.595

Appendix E. Censored Quantile Regression Estimates, Propensity Scores Tails Excluded.

Quantile	7% Cut Off		5% Cut Off		3.8% Cut Off	
	$\beta_{1\tau}$ Estimate (Effect of VAS)	P-Value	$\beta_{1\tau}$ Estimate (Effect of VAS)	P-Value	$\beta_{1\tau}$ Estimate (Effect of VAS)	P-Value
1	0.04	0.339	0.04	0.258	0.04	0.282
2	0.04	0.339	0.04	0.258	0.04	0.282
3	0.04	0.339	0.04	0.258	0.04	0.282
4	0.04	0.339	0.04	0.258	0.04	0.282
5	0.04	0.339	0.04	0.258	0.04	0.282
6	0.04	0.339	0.04	0.258	0.04	0.282
7	0.04	0.339	0.04	0.258	0.04	0.282
8	0.04	0.339	0.04	0.258	0.04	0.282
9	0.04	0.339	0.04	0.258	0.04	0.282
10	0.04	0.339	0.04	0.258	0.04	0.282
11	0.04	0.339	0.04	0.258	0.04	0.282
12	0.04	0.339	0.04	0.258	0.04	0.282
13	0.04	0.339	0.04	0.258	0.04	0.282
14	0.04	0.339	0.04	0.258	0.04	0.282
15	0.04	0.339	0.04	0.258	0.04	0.282
16	0.04	0.339	0.04	0.258	0.04	0.282
17	0.04	0.339	0.04	0.258	0.04	0.282
18	0.04	0.339	0.04	0.258	0.04	0.282
19	0.04	0.339	0.04	0.258	0.04	0.282
20	0.04	0.339	0.04	0.258	0.04	0.282
21	0.04	0.339	0.04	0.258	0.04	0.282
22	0.04	0.339	0.04	0.258	0.04	0.282
23	0.04	0.339	0.04	0.258	0.04	0.282
24	0.04	0.339	0.04	0.258	0.04	0.282
25	0.04	0.339	0.04	0.258	0.04	0.282
26	0.04	0.339	0.04	0.258	0.04	0.282
27	0.04	0.339	0.04	0.258	0.04	0.282
28	0.04	0.339	0.04	0.258	0.04	0.282
29	0.04	0.339	0.04	0.258	0.04	0.282
30	0.04	0.339	0.04	0.258	0.04	0.282
31	0.04	0.339	0.04	0.258	0.04	0.282
32	0.04	0.339	0.04	0.258	0.04	0.282
33	0.04	0.339	0.04	0.258	0.04	0.282
34	0.04	0.339	0.04	0.258	0.04	0.282
35	0.04	0.339	0.04	0.258	0.04	0.282
36	0.04	0.339	0.04	0.258	0.04	0.282
37	0.04	0.339	0.04	0.258	0.04	0.282
38	0.04	0.339	0.04	0.258	0.04	0.282
39	0.04	0.339	0.04	0.258	0.04	0.282
40	0.04	0.339	0.04	0.258	0.04	0.282
41	0.04	0.339	0.04	0.258	0.04	0.282
42	0.04	0.339	0.04	0.258	0.04	0.282
43	0.04	0.339	0.04	0.258	0.04	0.282
44	0.04	0.339	0.04	0.258	0.04	0.282
45	0.04	0.339	0.04	0.258	0.04	0.282
46	0.04	0.339	0.04	0.258	0.04	0.282
47	0.00		0.00	1.000	0.04	0.282
48	0.00		0.00	1.000	0.00	
49	0.00	1.000	0.00	1.000	0.00	
50	0.00	1.000	0.00	1.000	0.00	
51	0.00	1.000	0.00	1.000	0.00	1.000
52	0.00	1.000	0.00	1.000	0.00	1.000
53	0.00	1.000	0.00	1.000	0.00	1.000
54	0.00	1.000	0.00	1.000	0.00	1.000
55	0.00	1.000	0.00	1.000	0.00	1.000
56	0.00	1.000	0.00	1.000	0.00	1.000
57	0.00	1.000	0.00	1.000	0.00	1.000
58	0.00	1.000	0.00	1.000	0.00	1.000
59	0.00	1.000	0.00	1.000	0.00	1.000
60	0.00	1.000	0.00	1.000	0.00	1.000
61	0.00	1.000	0.00	1.000	0.00	1.000
62	0.00	1.000	0.00	1.000	0.00	1.000
63	0.00	1.000	0.00	1.000	0.00	1.000
64	0.00	1.000	0.00	1.000	0.00	1.000
65	0.00	1.000	0.00	1.000	0.00	1.000
66	0.00	1.000	0.00	1.000	0.00	1.000
67	0.00	1.000	0.00	1.000	0.00	1.000
68	0.00	1.000	0.00	1.000	0.00	1.000
69	0.00	1.000	0.00	1.000	0.00	1.000
70	0.00	1.000	0.00	1.000	0.00	1.000
71	0.00	1.000	0.00	1.000	0.00	1.000
72	0.00	1.000	0.00	1.000	0.00	1.000
73	0.00	1.000	0.00	1.000	0.00	1.000
74	0.00	1.000	0.00	1.000	0.00	1.000
75	0.00	1.000	0.00	1.000	0.00	1.000
76	0.00	1.000	0.00	1.000	0.00	1.000
77	0.00	1.000	0.00	1.000	0.00	1.000
78	0.00	0.000	0.00	0.004	0.00	0.000
79	184.38	0.000	0.00	0.000	118.99	0.000
80	616.74	0.000	629.71	0.000	686.12	0.000
81	1105.91	0.000	1194.04	0.000	1223.22	0.000
82	1501.39	0.000	1398.47	0.000	1000.37	0.000
83	1104.20	0.000	1228.02	0.000	686.79	0.000
84	1479.79	0.000	1485.39	0.000	1402.60	0.000
85	1273.34	0.051	1267.91	0.097	1321.20	0.035
86	38.83	0.938	−290.06	0.259	249.02	0.255
87	563.65	0.279	337.06	0.520	260.29	0.618
88	529.50	0.375	761.99	0.219	980.65	0.029
89	18.34	0.975	274.01	0.659	732.72	0.284

90	−847.35	0.272	−548.51	0.482	−76.61	0.907
91	−1249.40	0.077	−1013.10	0.162	−840.38	0.224
92	−2529.75	0.003	−2541.50	0.006	−1972.17	0.043
93	−3095.88	0.006	−3170.77	0.004	−2814.66	0.028
94	−3977.83	0.004	−4411.41	0.000	−3556.83	0.015
95	−4150.57	0.009	−3862.20	0.019	−3602.64	0.029
96	−2524.86	0.208	−2562.65	0.264	−1877.99	0.382
97	−1685.38	0.565	−1660.96	0.604	−852.57	0.783
98	−5970.84	0.349	−6746.68	0.290	−4535.20	0.473
99	−24875.49	0.798	−24669.74	0.799	−22662.15	0.815

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